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AI-Driven Transportation Systems: Real-Time Applications and Related Technologies

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This book is dedicated to my dear parents, Mr. and Mrs. Shoukat Iqbal, whose guidance and prayers have been my constant strength; my beloved husband, Mr. Muhammad Farooq, with all my love and gratitude for his unwavering support, which has been the cornerstone of my life, may Allah Almighty always bless us; my cherished siblings for their love and care; and my peers and mentors for their invaluable guidance throughout this journey.

—Hafsa Maryam

I dedicate this book to Allah Almighty, whose guidance and blessings have made this journey possible. To my beloved parents, Mr. and Mrs. Mushtaq Ahmed, for their unwavering support, prayers, and encouragement, and to my dear siblings, whose love and care have been my constant strength. I am deeply grateful to my peers and mentors, especially Sir Inam Ullah Khan, for *their invaluable guidance and inspiration throughout this endeavor. Your belief in me has been instrumental in shaping my path, and I owe this accomplishment to your support and encouragement.*

—Mehak Mushtaq Malik

I dedicate this edited book to my parents and sister.

—Dr. Inam Ullah Khan

This book is dedicated to my beloved parents and family.

—Dr. Shashi Kant Gupta

Preface

Artificial Intelligence (AI) stands at the forefront of technological advancement, offering unparalleled breakthroughs and transformative potential. As urban populations grow and the demand for mobility escalates, transportation systems face numerous challenges, including safety concerns, persistent congestion, real-time processing, security, data privacy, and environmental issues (i.e., high emissions). Intelligent Transportation Systems (ITS) have emerged as a solution to these challenges, offering innovative ways to optimize transportation networks. We are now at the dawn of a new era where AI is revolutionizing transportation. By integrating AI into transportation systems, AI-driven vehicles and systems analyze vast amounts of historical and real-time data, enabling informed travel decisions, providing real-time updates, and optimizing traffic management to improve network efficiency. Imagine a system where AI is embedded at the heart of every journey: predictive algorithms that anticipate and mitigate congestion before it occurs, re-routing traffic for optimal flow. Recent advancements in ITS rely on AI-driven algorithms such as machine learning (ML), deep neural networks (DNNs), and reinforcement learning (RL), which enhance safety, sustainability, and efficiency. These technologies empower transportation systems to make data-driven decisions, monitor traffic in real-time, and create smarter, more connected networks, paving the way for the future of transportation.

The book *AI-Driven Transportation Systems: Real-Time Applications and Related Technologies* delves into the dynamic integration of AI and ITS, highlighting the potential and challenges of bridging the gap between traditional transportation methods and modern AI techniques. It provides an in-depth examination of cutting-edge technologies, such as AI and the Internet of Things (IoT), showcasing their transformative impact on smart transportation systems. This book covers key concepts, strategies, and real-time applications, addressing critical concerns (i.e., security, smart parking, accident detection, intelligent routing, and traffic management). Ultimately, its goal is to improve driving efficiency, reduce congestion, and optimize network performance.

This book offers a forward-looking perspective on how these technologies will shape the future of ITS, positioning it as an essential resource for researchers, engineers, academics, and technology enthusiasts alike. We invite you to explore the innovative solutions, research studies, and multidisciplinary collaborations that characterize the cutting edge of AI and smart transportation research.

Representing the collective expertise of a diverse group of authors and contributors, this book offers unique insights and perspectives on the field. We hope it serves not only as a comprehensive guide to the current landscape of AI-driven ITS but also as a source of inspiration for future innovations in this exciting domain. May these contributions inspire further research, collaboration, and breakthroughs in the rapidly evolving field of AI and smart transportation systems.

We thank our readers for their interest and invite you to embark on a journey into the fascinating world of AI-driven ITS.

Happy reading!

Nicosia, Cyprus	Hafsa Maryam
Tartu, Estonia	Mehak Mushtaq Malik
Cyberjaya, Malaysia	Dr. Inam Ullah Khan
Selangor, Malaysia	Dr. Shashi Kant Gupta

Acknowledgments

The successful completion of this book, *AI-Driven Transportation Systems: Real-Time Applications and Related Technologies*, has been made possible through the collective efforts, support, and expertise of numerous individuals and organizations. We extend our sincere thanks to everyone who played a key role in its development and ensured the highest quality of its content.

First and foremost, we express our heartfelt gratitude to the authors and co-authors, whose invaluable research and insights have shaped the foundation of this book. Their dedication and expertise have been instrumental in creating a comprehensive resource on the integration of AI in Intelligent Transportation Systems. We also appreciate the review committee for their excellent cooperation, meticulous evaluations, and constructive feedback throughout the process, which have significantly enhanced the accuracy and overall quality of this work.

We are especially grateful to our colleagues at Springer Publishing Company for their continuous guidance and professionalism throughout the publication process. Their unwavering support has ensured that this book upholds the highest standards of academic and technical excellence. Additionally, we extend a special note of thanks to our academic community for fostering an environment of innovation, collaboration, and research excellence.

Lastly, we extend our deepest gratitude to our families, friends, and colleagues for their patience, encouragement, and unwavering support throughout this journey. Their belief in our vision has been a constant source of strength and motivation.

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Contents

Smart Cities Transformation: From Conventional Traffic Management to Artificial Intelligence AI-Enhanced Vehicular Ad-Hoc Network (VANETs) 1
Rupali Atul Mahajan, Rajesh Dey, Parikshit N. Mahalle, Vivek S. Deshpand, and Mudassir Khan

AI and VANETs in Smart Cities: The Next Frontier in Traffic Management 23
Babasaheb Jadhav, Mudassar Sayyed, and Shashi Kant Gupta

Next-Generation VANETs: Deep Learning, Machine Learning, and Secure AI Integration for Real-Time Urban Mobility 41
Fawad Ullah and Muhammad Ameer Hamza

Intelligent Route Navigation in VANETs Using Deep Learning 57
Rajesh Dey, Rupali Atul Mahajan, Mudassir Khan, Shaik Karimullah, and Barga Mohammed Mujahid

AI-Driven Security Mechanisms for IoT-Enabled VANETs 79
Bilal Ahmed, Arusa Kanwal, and Narmeen Shafqat

Securing VANETs for Internet of Things (IoT): AI-Driven Solutions for Privacy and Intrusion Detection 105
Tayyaba Basri

Evaluating ML Models for Intrusion Detection in Network and VANET Security 123
Muneeba Mubarik, Syed Nasir Mehmood Shah, and Umme Zahoora

Real-Time Vehicular-to-Vehicular (V2V) Communication and Applications for Pedestrian Safety in AI-Optimized VANETs for Autonomous Vehicles 151
Rupali Atul Mahajan, Rajesh Dey, Mudassir Khan, Kavita Kanabar, and Shashi Kant Gupta

Safety of Pedestrians in AI-Optimized VANETs for Autonomous Vehicles via Real-Time Vehicle-to-Vehicle Communication 169
Puja Gupta, Neeraj Arya, Chandra Prakash Singar, Amit Chaudhari, Upendra Singh, and Shrishti Gupta

Real-Time Surveillance System to Monitor Vehicles and Pedestrians for Road Traffic Management 183
Satish Kumar Satti, K. Suganya Devi, Naresh Babu Muppalaneni, and Prasad Maddula

Accident Detection from CCTV Surveillance Using Hybrid Vision Transformation and Alert the Nearest Hospital 209
Md Oqail Ahmad and Shams Tabrez Siddiqui

Featuring Smart Parking Solutions in Smart Cities: VANETs Optimization Using AI and IoT 229
Bhupinder Singh, Anjali Raghav, and Christian Kaunert

Optimizing Smart Parking in Urban Spaces: AI-Driven VANET Models Using IOT Frameworks 249
Hrishikesh Kokate, Babasaheb Jadhav, and Shashi Kant Gupta

Intelligent VANET for Smart Cities and Their Security Challenges 273
A. Bhavani, Vijayakumar Ponnusamy, S. Latha, A. Ramya, S. Diana Emerald Aasha, and Dilliraj Ekambaram

AI and IoT-Driven Smart Cities: A Centralized Approach to Urban Mobility 291
Abdur Rehman, Altaf Hussain, Muhammad Tayyab, Noor Ul Haya Farooq, and Syed Nasir Mehmood Shah

Intelligent VANETs—Machine Learning Integration for Enhanced Autonomy in Smart Cities 319
Manpreet Kaur and Vipin Kumar Chaudhary

Driving Intelligence: Deep Learning and Machine Learning Challenges and Innovations in AI-Enhanced VANETs 333
Wasswa Shafik

AI-Driven VANETs: Integrating Deep Learning and Reinforcement Learning for Adaptive Urban Mobility in Smart Cities 353
Muhammad Ameer Hamza and Fawad Ullah

Innovative Approaches to Urban Planning and Sustainable Development: The Role of AI-Driven Vanets in Smart Cities 369
Muhammad Usama, Ubaid Ullah, Zaid Muhammad, Muhammad Abbas, Muhammad Ameer Hamza, Muhammad Rouf, and Muhammad Bilal

Enhancing Urban Connectivity: Design Principles and Smart Solutions for Bridges and Highways 383
Muhammad Ameer Hamza, Muhammad Usama, Saad Ud Din, Ubaid Ullah, Zaid Muhammad, and Muhammad Abbas

Towards Resilient V2V Communications: AI Optimized Protocols, Performance, and Reliability in Autonomous Vehicles 395
Manas Kumar Yogi, Atti Mangadevi, B. Kalyan Chakravarthy, and Tarra Sekhar

UAVs and Federated Learning-Enabled Digital Twins of Vehicles in Dynamic Disaster Environments 415
Ehzaz Mustafa, Junaid Shuja, Faisal Rehman, Muhammad Bilal, and Muhammad Sajid Riaz

Performance Analysis of OFDM Techniques for Short Range V2V Communication 429
Mohammed El Ghzaoui

Smart Cities Transformation: From Conventional Traffic Management to Artificial Intelligence AI-Enhanced Vehicular Ad-Hoc Network (VANETs)

Rupali Atul Mahajan, Rajesh Dey, Parikshit N. Mahalle, Vivek S. Deshpand, and Mudassir Khan

Abstract Vehicular ad-hoc networks provide an entirely new way of wirelessly communicating between vehicles in cities. Such communication would eventually lead us to intelligent transportation systems in the transformation process of smart cities. VANET provides vehicular mobility in connectivity through wireless communication between vehicles and between vehicles and roadside units (RSUs) using the IEEE 802.11p standard. This paper summarizes and reviews the operation, applications, services, and conventional traffic management of some research work in VANETs. The techniques include the following: the design of delay-based energy-aware medium access control in VANETs, Virtual Roadside Unit Placement Assisted Communication, and a trust-based secure optimized routing framework for highway VANET communication. These frameworks have been designed using AI, and their performance is found to be superior because they reduce the time spent on travelling, energy waste, and traffic accidents. Further, these frameworks significantly reduce air pollution due to alleviation of traffic congestion beyond conventional methods although at an increased complexity.

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Keywords Vehicular ad-hoc networks · Route · Planning · Environment · Method · Deep · Proposed · Virtual roadside

1 Detailed Introduction and Overview

This article reviews and summarizes the operation, applications, services, conventional traffic management, and some recent research works on projects in vehicular ad hoc networks. There are numerous projects related to the VANET field. Although there are numerous projects, VANETs are applied to emergency warnings, information provision, assessing traffic volume, safety analysis, commercial advertising, and other applications discussed in this paper. We found some research to enhance the performance of VANETs from literature. The introduced methods include the design of energy-aware delay-based medium access control in vehicular ad hoc networks, Virtual Roadside Unit Placement Assisted Communication in VANET, and a trust-based secure optimized routing framework for highway VANET communication, among others.

Next, we briefly summarize the contributions of our research in this paper. The challenges of VANETs include security and privacy issues, communication channel problems, and the challenges posed by VANETs in urban areas and smart cities. The main contribution of our paper is to present a summary review of numerous applications and research projects, providing research ideas and the latest unpublished applications. We thoroughly review the research solutions and provide an overview of existing VANETs. Each of the accomplished projects and ideas is analyzed and presented through sensing, middleware, and applications of VANETs, including concerns surrounding VANETs and VANET simulation tools. Lastly, this paper serves as a bridge between researchers and the projects that have been achieved or will be undertaken in the future. Our proposal can help promote research in the VANET area.

1.1 Background and Significance

Nowadays, mobile technology has become better and integrated into the products and services for providing a well- connected, easily accessible environment. Emerging mobile technology has an incredible impact on transforming not only the way people are connected but also how cities are operated and managed. A smart city implies the implementation of a network of sensors to monitor various parameters, such as air quality and traffic monitoring, to manage and control public infrastructure as well as the usage for the provision of necessary services. The capabilities of software and suitably deployed sensor networks allow for control and reporting of anomalies related to managed infrastructure, which eases decision-making in managing the city infrastructure along with the services. The majority of smart city initiatives focus mainly on the technological advancements in urban design and infrastructure, labeling cities as high-ranking through global visibility, brand name as a place, and innovation through smart technology applications. There is no common understanding of the term 'smart cities,' delivering a different image.

Substantial research effort and work on the development of smart mobile appliance creation, enhancement, support of environment, services, and applications have been carried out utilizing various devices, networks, and protocols. The concept of the Internet of Vehicles is used to enable mobile communications, location, and tracking technologies, routing, and the capability of deploying and collecting data. Vehicular Ad Hoc Networks are considered a subset of ad-hoc mobile applications and communication networks, which focus on transforming vehicles into mobile sensing units. The vehicles in VANETs send messages for sharing information in the non-scheduled mode or dynamic routing based on the vehicle's location and movement patterns. Such attributes of VANETs can result in efficient traffic management, improved communication resource utilization, and other public services. In this paper, the main traffic management tasks that are collectively addressed can be classified into three levels. First, vehicle localization and tracking. Second, message forwarding between vehicles or between a vehicle and the roadside infrastructure. Third, signal control management as well as a combination of them [1].

1.2 Scope and Objectives

The existing traffic control systems, including the advanced intelligent traffic control systems, are typically managed by the centralized control centers for road networks in each city. Ad hoc vehicular networks have attracted a lot of attention regarding traffic congestion problems detection and solutions. It is the most specific use of the new widely recognized artificial intelligence concepts. These intelligent vehicular networked systems are designed for autonomous control by themselves. Through the automobile communication technology, we advocate that the city regional transportation network can be transformed into individual intelligent entities produced by AI. They are not only for autonomous control, avoiding traffic jams and collision accidents, but also for preventing contagious diseases transmitted in the traffic systems.

Autonomous and intelligent transportation functions can be divided into two categories. The first category focuses on the immediate on-site detected traffic-ejection operations with health and safety in mind. This is the ad hoc vehicle ejection network transportation control system. The second category pays attention to relevant intelligence information about high-risk driving and potentially dangerous road conditions, such as weather conditions, closed roads, and contaminated areas. All of which would harm the people who interact with the transportation flow somewhere soon. Based on the current contact in the traffic flow and the road conditions caused by communication technology, a reportable risk list affecting people's health and safety includes traffic injuries caused by high-risk driving conditions and potential or immediate contagious or infectious disease transmission in the transportation network [2].

1.3 Understanding Smart Cities

Smart cities transformation has been attracting research attention on the redesign of traffic management systems using vehicular ad-hoc networks. However, how smart a city can be achieved by such technology has not been addressed. This paper starts by discussing the importance of understanding the concept of a smart city before implementing smart city projects like VANETs. We then present the transformation path of a smart city. According to the existing constraints and the local needs, the first transformation is the upgrade of the conventional traffic light control system, which saves energy and reduces fuel consumption [3].

What is a smart city? What can it be from the point of view of information technology? In a smart city, digital technology is used to enhance performance and well-being, to reduce costs and resource consumption, and to engage more effectively and actively with its citizens to improve the city's assets. A smart city is one in which digital technology is used as an enabler to create effective, efficient, sustainable, and inclusive urban environments: smart is when investment in human and social capital and traditional and modern communication infrastructures fuel sustainable intellectual capital and, hence, innovation and economic development. The ultimate goal is to establish an intelligent economy.

1.4 Definition and Characteristics

The term "smart city" is a well-known term in both research and practice, having been adopted not only in IT and engineering sciences but also appearing in other areas of study. Smart cities have been the object of cultivation by politicians, investors, scientists, and professionals as a new alliance of domains for urban spaces that combine data with the Internet of Things and Big Data processing to plan and develop cities where smart citizens can be comfortable. The main aim of a smart city is to improve the quality of citizens' lives by enhancing the quality and availability of infrastructure through the application of smart technologies [4].

One important consideration about smart cities is the transformation of conventional traffic management into smart city traffic management. Hence, considering the non-linear characteristics of fluid traffic in urban areas, the utilization of traditional traffic management concepts with enhanced AI concepts is important. The significance of the fundamental characteristics, architecture, and features of AI-enhanced VANET has been discussed in the earlier section of this paper. A smart city application model highlights the path of a vehicle dropping off or picking up passengers at the assigned bus stop in urban traffic. Pedestrian traffic management using ACR methods and WiFi data mining to boost a smart bus system has been investigated. In addition, smart city connecting factors comprise smart infrastructure combined with a traffic management plan [5].

1.5 Key Components

As its name indicates, an intelligent VANET is a set of high-technology agents or nodes employing highly advanced and flexible AI algorithms. An intelligent VANET is built mainly on four types of principles: interaction intelligence that supports cooperation or negotiation of involved agents in the VANETs, cognitive intelligence that supports the intelligence of every single agent's behavior and learning process, data intelligence or knowledge intelligence, physical intelligence that supports the mobility, stability, and capacity of a single agent, and middleware intelligence that supports the intelligent micro-agent or groups of micro-agents-based mechanism. The intelligent VANET system is designed as two main agents. The first agent is a data relay agent that directly connects and communicates with its associated vehicle or RSU through an ad-hoc communication system. Inside the vehicle, its information is retrieved and transformed into a network message packet, and its self-identity data will be automatically released to the VANET visual intelligent subsystem. In the meantime, the vehicle's camera uses the released image taken by its camera to check the road status. The road status checking is repeated every instant. The road status data is joined with the vehicle's own status message and data relay message under one control unit. In essence, this agent is mainly a coherent mobile part to support the intelligent driver style-based applications.

The second agent is the VANET visual intelligent subsystem that performs real-time image and video processing using two levels of intelligence: model-based learning and actual video processing. The system intelligently releases different image models, templates, and image distributions that are stored in the distribution database and continuously updated by the intelligent learning control unit. The collected image and video data and its intelligent computing results are then combined with other traffic information to provide useful control, management, and guiding information [6].

Additionally, the subsystem can be used to assist different ad-hoc applications, such as information systems, intelligent car systems, traffic infrastructure smart control systems, and more advanced V2V applications. The VANET visual intelligent subsystem is particularly focused on the convenient computation of each image by seeking to meet the critical performance indicators, such as the image global segmentation and application correlation coefficient to present detection accuracy for image and video database use over a long period. In summary, the output or organized content of the VANET visual intelligent system provides both network intelligence and agent intelligence. The highly advanced and flexible intelligent system can significantly support the convenient deployment of intelligent VANETs [7] (Fig. 1).

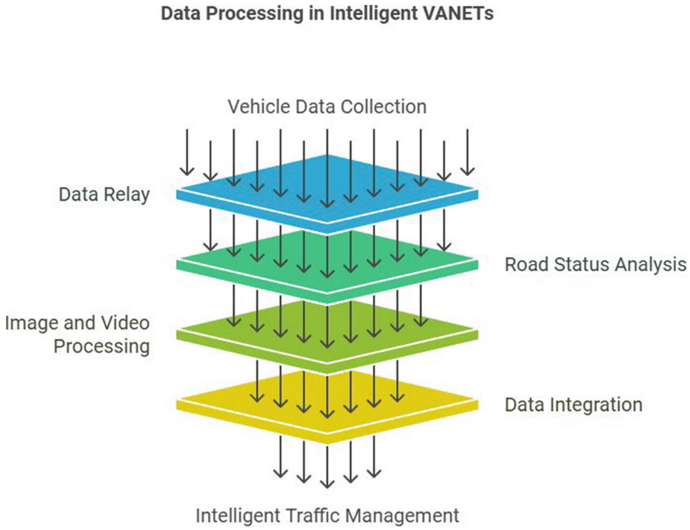

Data Processing in Intelligent VANETs
Vehicle Data Collection
Data Relay
Road Status Analysis
Image and Video Processing
Data Integration
Intelligent Traffic Management

Fig. 1 Data processing in VANETS

1.6 *Conventional Traffic Management Systems*

With rapid development in recent years, various systems and techniques have been developed to analyze traffic-related data and help people make decisions. The simplest way to manage traffic is to designate traffic personnel to control traffic lights. Subsequently, car-sensitive electronically controlled traffic lights are increasingly employed with the development of technology. However, these methods need a large number of traffic personnel, and their traffic control cannot be optimized, especially during severe traffic congestion. With the development of computing technology, researchers are beginning to employ computer vision, especially deep learning algorithms, to learn and analyze traffic data from stable public cameras. Additionally, transportation information systems are used to analyze this data and provide traffic suggestions to help citizens in the event that population dislocation happens [8].

With the rapid growth of connective devices and communication technologies, a new method called context- aware traffic light control is proposed for vehicle-to-infrastructure communication. The connected vehicles will send a message to the Edge Computing Server with information such as road conditions and driving preferences. Then, this method will calculate the duration and time of red, green, and yellow phases for each lane in each direction according to the information and the control policy. Additionally, delay time, queue length, number of stops, average speed, and loss functions are some of the indicators that can be used to evaluate the performance of the algorithm. These indicators can effectively optimize traffic lights to achieve the purpose of reducing traffic congestion and increasing traffic efficiency. Since there may also be blind spots caused by road construction and occlusions, this method has also used clustering to achieve constrained synergistic optimization for traffic light control.

1.7 Challenges and Limitations

Current traffic management systems include green light optimization, lane counting, road signaling, incident pre- diction, and traffic information systems that provide real-time information to drivers about the current environment and more, under the scope of traffic demand management and congestion charging systems. However, the key challenges faced by today's urban traffic management and road sensor systems are the lack of scalability, high cost of deployment, lower battery backup solutions, and security and privacy issues. Particularly, traffic and congestion management are unique and complex challenges in a big city. Such issues can only be solved by a detailed and accurate road vehicular environment interaction information model. To build a transportation system that is truly smart, efficient, sustainable, safe, and accessible, it involves intelligent transportation infrastructure that connects vehicles with each other and with the infrastructure around them, sharing information in real time to avoid traffic accidents, reduce congestion, minimize travel times, costs, and environmental emissions, and improve customer experience and satisfaction. The implementation of intelligent transportation systems using vehicular ad-hoc networks has been recognized as a promising strategy and potential solution to transportation safety and congestion problems. These networks can provide public safety communication and completely transform traffic flow in cities into a seamless cooperative service with low cost, but with high efficiency and sustainability. They provide vehicles with intelligence to make safe decisions concerning priority assignments to manage traffic flow effectively, protecting lives and property. However, these networks also have several challenges that need to be addressed, such as traffic flow management, which are specific to the field of traffic monitoring and control [9].

1.8 Evolution and Current State

Over the past two decades, transportation systems globally have evolved from traditional traffic management to the Internet of Vehicles, with the development of vehicular networks such as VANETs and Vehicular Cloud Networks. However, despite the transformation of mobility, both VANETs and VCNs suffer from major limitations such as communication link instability, scalability issues, and the lack of efficient network security. This necessitates extensive research in VANET and VCN technologies, allowing a stable, efficient, reliable, and secure communication network between vehicles and the cloud, focusing on conventional traffic management, artificial intelligence, VANET, VCN, and conventional traffic management with AI-enhanced VANETs in this work.

Deep learning and reinforcement learning are implemented to develop AI-enhanced VANET frameworks to solve different conventional intelligent traffic management problems such as traffic congestion, traffic accidents, air pollution, and wasted energy. Reinforcement learning is employed to optimize the routing between the Roadside Units and VCN, while deep learning algorithms are utilized to develop vehicle smart control models for controlling the trajectories of self-driving vehicles. It is found that the designed AI-enhanced VANETs have better performance in terms of reduced traveling time, reduced energy waste, fewer traffic accidents, and air pollution, alleviating traffic congestion more effectively than other conventional methods, at the cost of increased complexity. It is suggested that a decentralized or hybrid model should be designed to lower the complexity.

Introduction to Vehicular Ad-hoc Networks (VANETs the integration of ANETs with AI technology can significantly enhance the overall management of conventional traffic-condition-based road networks, not only in terms of ensuring road safety but also in terms of minimizing the impact of accidents and ensuring roadability conditions. In this chapter, AI enhancement of a conventional VANET consists of two parts: Image Pattern Recognition and Real-Time Deep Learning AI Technology. Unlike conventional quadraphonic or multi-dimensional VANETs, the most significant difference is that our model consists of various commercial products equipped with IPR and mobile VANETs, which can track with ADAS and provide real-time data transmission through 4G, 5G, or similar technologies. Furthermore, we have coordinated conventional drone technology through AI Deep Learning. We further propose an AI model that significantly improves the conventional image pattern recognition of various descriptions and AI-based data transmission problems caused by limited resources or the high data volume requirement of mobile VANETs. We also show benchmark performance results under filter techniques from publicly available data sets. The performance of our proposed approach, when applied to public datasets, leads to an average Denoise CNN Image Classification Accuracy Rate of 96.8% and a DNN with an Average Time Performance of 0.07 [10, 11] (Fig. 2).

The dramatic increase in the number of vehicles, traffic volume, injuries, accidents, or roadable weather conditions in terms of safety potential and economic value has given rise to demands for wider-ranging safety management by road operators. The vehicle network systems of both centralized and point-to-point, also known as Intelligent Transport Systems, mainly function by processing information collected from individual vehicles and roadside-based sensors. The rapid development of computer networks, such as broadband Internet and bound- less geographical telephone systems, has led to demands for providing users with broadband service connectivity. Ten major vehicle manufacturers have developed vehicle network systems using VANET technology. However, autonomous vehicles also require a high bandwidth service to accomplish the task of providing users with convenience and safety. Since drones and ground systems can skip, hop, and jump, and are inexpensive, we propose a new vehicle ad-hoc system model capable of significantly capturing the high bandwidths required by autonomous vehicles [12].

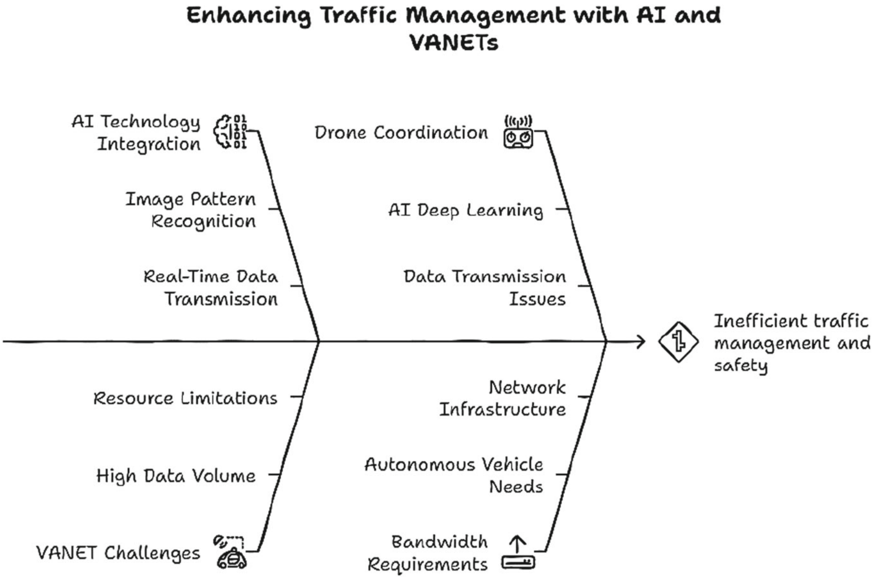

Enhancing Traffic Management with AI and VANETs
AI Technology Integration
Image Pattern Recognition
Real-Time Data Transmission
Drone Coordination
AI Deep Learning
Data Transmission Issues
Inefficient traffic management and safety
Resource Limitations
High Data Volume
VANET Challenges
Network Infrastructure
Autonomous Vehicle Needs
Bandwidth Requirements

Fig. 2 VANETs traffic management

1.9 Definition and Key Concepts

With the advancement of technology in communication and wireless networks, the development of smarter public transport and intelligent transportation systems (ITS) through connecting vehicles together and integrating data from different sources, such as traffic management systems and applications of traffic and public transport, can certainly be realized. This text attempts to provide a comprehensive review of the vehicular ad-hoc network (VANET) communication technology that enables wireless communication between vehicles in urban areas, contributing to intelligent transportation systems (ITS) in realizing smart city transformations. The aim is to promote VANET technology to the broader community, particularly the public, developers, researchers, and practitioners in the field, in realizing the time to travel in near-future smart cities. VANET is a special kind of mobile ad-hoc net- work (MANET) created by applying technology to vehicular networks, enabling connectivity through wireless communication technology between vehicles and between vehicles and roadside units (RSUs) using the wireless communication interface of IEEE 802.11p.

The key features of VANET compared to ad-hoc networks include fast topology changes with a moderate number of nodes, relative differences in the speeds of the nodes, and communication range and location information of the nodes. The existing VANET standard IEEE 802.11p was proposed and mainly designed to deal with safety and autonomous driving in vehicular environments. As communication technology evolves along the history of development, VANET has been extended to incorporate non-safety-related applications to form a new vehicular communicative system that further enhances driving and social experiences. Their key differences demonstrate several advantages over traditional data modem-based systems, including low delay, high reliability, and spectrally efficient communication, which are particularly important in VANET safety applications [9, 11].

1.10 Applications and Benefits

The development of smart cities promises to deliver efficiency and sophistication in city operations by using technology that can improve the quality of citizen welfare. This can be accomplished by optimizing the use of resources to minimize environmental impact and ensure sustainable development. With the development of machine learning and artificial intelligence, traffic problems can be addressed by harnessing these technologies. The intelligent VANETs through AI have mature capabilities to solve problems dynamically. We discuss the development of AI-enabled VANET for the transformation of traffic control and management and the benefits that have been achieved. The widespread deployment of AI-empowered VANET enables a number of applications that enhance traffic safety, traffic efficiency, and journey experience. Most road accidents can be avoided by using smart AI- empowered VANET. Road assistance is deployed based on predicting the future location of the requester; this is important as it is an essential safety disclaimer for drivers. Time and fuel will also be saved, reducing the likelihood of secondary accidents occurring. Improved traffic control through intelligent VANET can alleviate congestion by shifting a collective transmission schedule in a timely manner, introducing diversions, and eventually clearing trouble-prone road sections, leading to social welfare benefits. This can also reduce air pollution in cities.

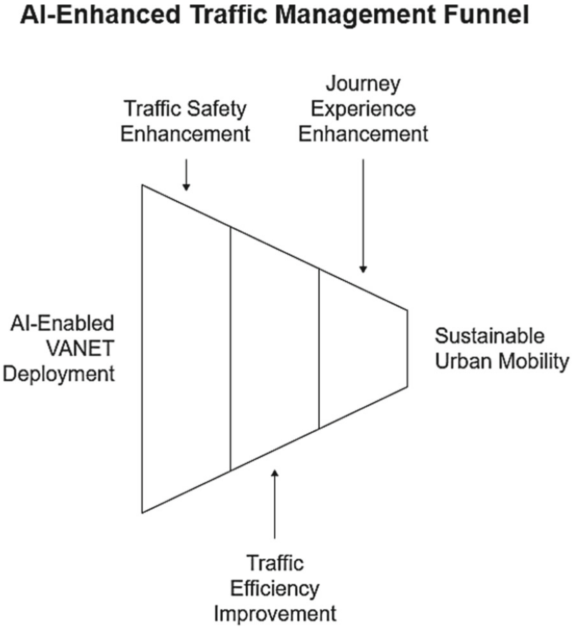
These benefits can ultimately reduce the demand for road capacity expansion. Research has also shown that the implication of AI-enhanced V2V networks has the potential to prevent up to 40% collisions.

1.11 Artificial Intelligence in VANETs

The purpose of this section is to develop a comprehensive understanding of artificial intelligence in vehicular ad-hoc networks (VANETs) in the smart city context. It synthesizes various definitions and concepts. It is also aimed at outlining the importance of artificial intelligence in VANETs. Broadly, VANETs are an established part of traffic management. The security issues have also been addressed at some level (Fig. 3).

Artificial intelligence (AI) has evolved our lives considerably in the past few decades. Intelligent machines are working alongside humans to enhance the abilities of people on the planet. They are doing routine jobs. But in addition to this, AI

Fig. 3 VANETs traffic funnel


AI-Enhanced Traffic Management Funnel
Traffic Safety Enhancement
Journey Experience Enhancement
AI-Enabled VANET Deployment
Sustainable Urban Mobility
Traffic Efficiency Improvement

machines are also being used for problem-solving in various fields, e.g., for traffic management, predicting weather, healthcare, etc. AI has the capability to support different applications like the Internet of Things, VANET, public transport, healthcare, etc. Artificial intelligence (AI) in VANET research perspectives has its own importance. It is utilized for management, controlling, monitoring, estimating, or predicting purposes. AI algorithms can work for people in the world of VANET in many different ways. AI-enabled VANETs can estimate or predict traffic jams in the city and offer alternate routes to eliminate time wastage. People in vehicles can get helpful and meaningful road congestion information from the system. In this way, AI enables VANETs to plan, manage, and control traffic more efficiently and effectively [13].

1.12 Overview of AI

According to its definition, artificial intelligence (AI) is based on a combination of complex computer science techniques including knowledge representation, case recording, random variables and probability, cognitive modeling, and so on. While the researchers in AI helped to transform the goals of science, such as understanding intelligence as part of the universe and its study by building models of thinking, over many years we have drawn a number of lessons from numerous attempts, many of which have been both theory and experiment. These lessons do not fall neatly into scales; they cross many topics and phenomena as they come from a more complex world. Some- times the ideas may seem contradictory or inconsistent. These are the narrative notes gathered from a number of enterprises to understand the problems of intelligent systems, not to solve them. The computer AI program made history by beating the world champion at chess. However, it still has difficulty understanding and simplifying hu- man language, which is much simpler and easier. AI programs can create other programs and machines with little assistance from engineers. They can learn from experience through formal and informal trial and error processes and be more effective than humans. The successes in these areas led to the development of two basic fields of AI: machine learning and neural networks. Early programs that used this neural network approach included an autonomous helicopter, handwriting recognition, and a continuously adjusted gearbox. AI programs usually excel compared to people in situations that are not possible or dangerous, or when computer code offers not enough memory and other mechanical constraints [12, 14].

1.13 AI Techniques in VANETs

All the above heuristic-based algorithms have used the same mundane traffic with the same percentage of vehicles modified to become selfish vehicles. The number of cohorts having different selfishness percentages has caused traffic jams on the highway. The auxiliary information provided by the owners of the selfish vehicles about their movement plans has not enabled the algorithm to perform any better than the simple greedy one for WSCI, intelligent OPT, DCl-P-MID, and DAg-P-MID. The microscopic simulation model used in this work has not allowed us to demonstrate the superiority of the communication constraints-aware, heuristic-dedicated approach for selecting the fail-safe cohorts, including selfish vehicles on highway DAg-P-MID, the last one being the main downside of the work. SMIA-DCL does not support a fail-safe nature with congestion kick at all but does provide a transmission time adjustment mechanism. SMIA-DAg, all three mechanisms working in e-DSR, are no-go.

GAB-I-MODAS, Q-GASA, IHV-ULS, ROD-DCL, IHV-DCL, WSCI-DCL, IHV-Dag, ROD-Dag work with any VANET MANET protocol correctly. Several different highway scenarios have been conducted; the characteristics of WSC-DMCAST increase this protocol's appeal. GAB-I-MODAS, Q-GASA, IHV-ULS, ROD-DCL, IHV-DCL, WSCI-DCL, IHV-Dag, ROD-Dag, and WSC-DCL do support a fail-safe nature, but DCl-P-MID and DAg-P-MID have higher goal values when they can only service non-selfish vehicles online, incapable of helping people absurdly due to transmission time limitations. SMIA-DCl and DAg provide mobility patterns that can be used by augmented approaches as well as better goals upon assigning tasks from a base which a more sophisticated approach proposes. The approaches would exist that adjust schedules.

The simulation models have shown that the congestion behavior of all greedy approaches can be anticipated by each of the AI-augmented methods and a middle-ground solution. In summary, every non-greedy approach can handle traffic jams and facilitate controlled rule changes that would increase performance beyond the greedy ones. No other association has addressed this issue because, as it seems, no one else has even conceived of it. In summary, only SMIA-DAG provides all ethically correct schedule prioritizations, the same time constraint information, fail-safe functionality for negligent and selfish vehicle supplementation, the e-DSR support, and the still-to-be-optimized helper information deadlines divided between the two types of driver-owned dispatch behaviors within the methodology [15, 16].

2 Effect of Selfish Cohorts on Highway Traffic and Algorithmic Performance

The presence of several cohorts with different levels of selfishness has inflicted a significant level of traffic congestion on highways. In the vehicular network, selfish vehicles are paradigm-based movers, ranking their own goals above system-wide efficiency and flow in the highway traffic pattern. The challenge is therefore in designing proper algorithmic ways to handle these vehicles and yet maintain a failure-safe system. Yet the study concluded that there is no help from the models of selfish vehicle owners in the form of auxiliary information regarding their future movement plans beyond that conferred in a basic greedy scheme.

Even though the MCEITA has W-SCI (Weighted Cohort Integration) listed, Intelligent OPT (Optimization-oriented approach), DC1-P-MID: Dynamic Cluster-Based Partial MID, DAg-P-MID: Dynamic Aggregation-Based Partial MID, these traffic management algorithms envisage improved traffic efficiencies while driving at the cooperation and selfish levels of vehicular behavior. That, expectedly, never saw the day of light; it has got to attribute mostly because the algorithmic efficacy of these models cannot fetch extra information from signal inputs gathered by real-time applications.

Limitations of the Simulation Model

When the microscopic simulation model explained not to discourage the faultless communication constraint-wise and heuristic-dedicated appraisals in a cohort-trimming selection, particularly towards selfish vehicles, but instead exalted those methods one and all, the focus truly felt so dry. Microscopic models mostly simulate vehicular movements rather than broader traffic patterns, typically mannering detailed interactions. Not being able to demonstrate a single effective way to apply heuristic-guided techniques suggests that either the granularity of the simulation reaches its extreme limit or that the vehicle communication is too restrictive.

In the exploration of these four approaches, shortcomings of DAg-P-MID were very conspicuous among the selfish vehicle cohorts, marking a severe deficit in this study. It suggests that in order to completely appreciate the dynamic interactions between selfish cooperative vehicles, a more flexible or hybrid approach, which could integrate both macroscopic and microscopic views, is needed.

Evaluation of Road Scenarios as Well as Protocol Effectiveness

To determine the protocol's real-world applicability, several highway scenarios were set up. In the studied ones, WSC-DMCAST was found to be more favorable. However, in comparison with DCl-P-MID and DAg-P-MID, which gain higher values of goals when only non-selfish vehicles are used under their supervision, fail-safe approaches turned out to be more robust:

These protocols inherently possess fail-safe methods to ensure system functionality in the presence of selfish vehicles. However, DCl-P-MID and DAg-P-MID are greatly hampered by transmission delay restrictions, thus rendering them very ineffective in dealing with mix-traffic scenarios.

1. Selfish behavior by vehicles impedes traffic development and is a principal problem for traffic optimization algorithms.
2. Further adaptive or predictive mechanisms are needed to be achieved through additional data from selfish driving beyond the basic greedy methods.
3. The acceptance of the simulation model at microscopic level calls for some rethinking, given its inability to show the benefits associated with heuristic approaches, urging much-improved modeling for communication and stronger decisiveness on behalf of the agents.
4. WSC-DMCAST and similar fail-safe protocols show strength and resilience in mixed road conditions, and DCl-P-MID and DAg-P-MID weaken due to time delays.
5. For future studies, establishing simultaneous hybrid simulation models, coupling better microscopic perspectives with macroscopic projections in real-time adaptive applications, still has to be considered.

2.1 Integration of AI in VANETs for Smart Cities

Future vehicular networks have a significant role in smart city applications, where artificial intelligence methods could be integrated to enhance the performance of a smart vehicular network. Traffic congestion is the most significant issue faced by a smart city, and it influences vast socio-economic variables, creating pollution and energy waste. Over the past few years, many solutions have been suggested using different types of sensor technology with traditional communication approaches. However, the lack of global standards for such networking and their high deployment and maintenance costs suggests that to maintain and manage the currently available communication infrastructure, one could explore the potential of existing vehicular ad-hoc network architecture using AI.

In this chapter, the communication and control infrastructure of a smart city is presented in a way that leads to a vehicular communication network and a novel system using an agent-based approach. Two different scenarios are integrated separately for effective traffic management, where shared control theory is also used. The system architecture of the proposed solution presents different levels of authority for the agent, with a lower level using dedicated short-range communication for vehicle-to-vehicle, vehicle-to-road, and route-to-vehicle communication. The agent-based object-oriented modeling of the vehicular communication network is presented, including the behavior of the architecture. The concept and application of the proposed solution in smart cities are studied in this work, which will provide guidance for the deployment of the technology in future smart cities. The developments introduced in this chapter could have important implications for stakeholders in smart city applications. User satisfaction, transportation costs, travel time, drive time, vehicle speed, and fuel consumption are compared based on complex network dynamics and network capacity, while the energy emergency distributions are presented as a preliminary step to integrate an AI-enhanced system into commercial, off-the-shelf ad-hoc network architecture. The algorithm designs and computer simulations correspond and validate the system and transmission models of the technology, while further work needs to be carried out to ensure market acceptance. The applications demonstrated in real scenarios, the multi-agent imitation, the software design, and the vehicle prototype also need to be completed as future work [17, 18].

2.2 Benefits and Advantages

By applying AI to VANETs, the information exchanged among vehicles, such as GPS coordinates of the destination points, routes, or traffic flows, can be analyzed and predicted to provide correct decision-making suggestions to the drivers regarding traffic flow, all in real time. As a result, road safety for all users of intelligent transportation systems can be improved. The methods used to exchange GPS information for vehicular travelers, display route options, publish travel itineraries, or optimize which path should be used might differ from system to system, but in general, the ability of people to travel safely and efficiently will be much better in the presence of an accurate framework of intelligent vehicular traveler assistance solutions that communicate and share information to provide the correct service. In the following section, the primary use cases as a benefit of combining AI techniques with VANET are summarized.

With the advent of AI, all participants in traffic can solve emerging problems more efficiently. Car congestion on arterial roadways and freeways decreases when car and truck traffic flow is made step by step easier, allowing users to operate their route plans based on the exchange of GPS information. Priority-based throughput can move important travel events easily. Commercial transportation is able to make efficient use of its available resources. In addition to traditional vanpooling, people will be able to share rides more selectively. Bus and rail services will be more successful in both generating user demand and attracting advanced users.

2.3 Challenges and Considerations

The introduction of AI into VANETs leads to a more robust and technologically advanced structure. Nonetheless, the collection and usage of vehicle-generated data raise questions about safety, security, and privacy. This sudden growth will most likely bring about new architectural forms of trust and automotive validation. When VANET encompasses an installed environment, the type of safety policy and implementation to be pursued will become a distinct debate. This discussion includes imposing security constructs in a secure environment that meets certain laws. The introduction of high-level vehicle connectivity technologies and systems, highly automated vehicles, and smart material systems capable of listening to and reacting to data transmitted over various distances around and among vehicles may cause individual security and surveillance concerns. For instance, it will be feasible for vehicles to detect whether each other is trying to jam either V2V or V2I in the future.

As a result, the parties could claim that surveillance biometric data collected on the VANET is at a high enough level of awareness and that their constitutional rights concerning mobile technology, computers, and cyber networks are affected, including the restrictions that prohibit a mobile electronic system from intercepting a communication for public, a vehicle's communication system from intercepting identical vehicle communication, or an entity from intercepting or spying on them for their vehicle or their communication or location data. This issue will become even more complex as vehicles are preloaded with passenger negotiation protocols and become personal electronic devices, thus framing this as a mobile security puzzle.

2.4 Case Studies and Examples

The following section is an overview of case studies and examples of recent research enhancing traffic management in smart cities with AI within VANETs. However, advanced technologies far beyond AI, including ML, VL, and DC, are also capable of enhancing VANET to different levels to enable better communication performance, more robust and reliable safety, and convenience services. On the other hand, current AI-based VANET systems and future research enhancements mainly focus on vehicular environments. Conversely, the roadside and road- intelligent service enhancements under AI that could also enable road service to provide, assist, or even override certain MANET environment services, safety, and convenience are less focused on and addressed. Looking ahead, a cross-level AI and AI-network-enabled VANET will eventually help to converge both vehicle and road environments and service enhancements and provide an intelligent overall system to serve the passengers and road services for smart cities.

Presented is further an overview and categorization of our snapshot case study examples on current AI-enhanced VANET infrastructure and/or services in progress of our literature review that often seem to indicate researchers are not aware of the various multiple levels of AI technologies which are suitable to enhance VANETs for better service and better vehicular communication environments. A cluster-based AI approach to enhance multi-critical data forwarding among different clusters in VANETs: This is an AI-enhanced selective forward algorithm for multi-type critical traffic data, with stand-alone clusters applying AI to enhance the MANET performance. The AI decision is performed at the cluster head in standalone clusters with synchronization between cluster heads, and an AI-based forwarding model is constructed on the selected data relay vehicles considering multiple influencing factors including connectivity stability, data transmission distance, and the probability of successfully receiving the multi-critical traffic data. Based on the Timer–Energy Control Model and Alert Service Model, and taking into considering road type and vehicle speed, the data forwarding decision-making is divided into different decision-making models. This is my first attempt to address the highly dynamic routing mechanism where each participating vehicle needs to satisfy the data propagation delay and stability of the constructed routing through a simple energy consumption control model. The AI model performance is evaluated by using several influencing factors.

2.5 Successful Implementations

In this section, a review of various MEC or AI-based services enabled on VANETs, as well as some network structure or function enhancement proposals, helps elucidate both the challenges and recent solutions of high- performance VANETs. The road from the intersections of Hillsborough and Hearst streets, in front of the University of Miami, is equipped with small cell tower technology, which will accelerate the development of smart cars and other smart projects in Miami, including rapid response to traffic safety, hurricanes and tsunamis. This is the world's first commercially deployed small cell technology structure.

A small cell tower was built in Miami in 2017. The four major telecommunications companies launched their own small cells on Brickell Avenue and are now using a carrier designed for future autonomous driving, in remote and automatic parking. Enables new and existing vehicles to communicate with each other and the surrounding infrastructure. Since 2018, there is also a Volkswagen atsuarevanet. Car communication devices and parked cars will be able to notify the vehicle approaching when they are going to leave a parking space, allowing the vehicle to park automatically. This paper believes that the development of smart cars should base all expectations on discussing the roads through which to cooperate, thereby achieving more specific concepts of new car projects in the future, instead of expecting automotive manufacturers to mass-produce self-driving cars first.

2.6 Lessons Learned

As per the feature claims received, the developed solution completely fulfills all functional and security requirements set in the smart city. The spatial resolution of the utilized data is proper and currently satisfactory for the needs of our services. The pilot nature of this solution enables us to present many existing implementations path troubles. However, they were addressed as occurring, and their resolution shows that smart traffic services are feasible to be implemented in a wider spatial and temporal context.

The evaluation of the developed system provides an overall assessment of the developed infrastructure and solutions. Reflected on the experience gained, our findings suggest wider applications of VANETs and multi-agent systems in smarter city verticals. The results obtained also outline future steps for city council policy development regarding parking places and restrictions on usage in the most congested city area's pedestrian and vehicle detection. Although the tested configuration has several limitations, the applied requirements and principal design are innovative and flexible enough to allow for their extension, thus suggesting directions for further development.

2.7 Future Trends and Innovations

Both physical and social Smart City digital domain layers have data security and privacy protection concerns. Many threats and vulnerabilities exist in futuristic VANETs with 5G. Services may be resolved using AI and other advanced technologies. There are also several emerging technologies that can be integrated with AI to enhance the vehicular network functionality. These include the use of parallel V2X convolutional neural networks that are able to transcend road network infrastructure constraints by using machine learning to handle vehicular data. The combination of AI and information-centric networking can form the ICN-VANET driver assistance system. The exploitation of bio-inspired neural networks, where the dendrites in the neurons have the ability to learn and recognize patterns, is also significant. Complex problems and data may be solved by using large, deep, and multilayer artificial brain networks that can iteratively and adaptively perform data classification. This approach may be used by governments to predict traffic demand.

Reductions in spectrum and energy, improvements in security and privacy protection, and mitigation of performance and cost due to complexity and multiple users of 5G networks, along with the incorporation of automated vehicles, the Internet of Things, and the Internet of Vehicles; big data storage capacity and handling; and smart city decision support systems and applications are a few major future challenges that must be addressed in the cities of the future, managed in autonomous and assisted manners. AI and advanced technological solutions are also able to offer new pieces of information and new functions to the Smart City by developing a network system that is data-aware and able to recognize data as more than just bits and bytes, embedding additional information into data and deriving useful information from semantically named data items. When devices are able to use ICN directly, they will have the capability to process data quickly. Therefore, it is important to develop a data process at the core of the AI algorithms. The future fully AI-empowered VANETs will utilize well-placed mobile nodes and social IoTs to collect every bit of additional physically and socially important data to derive a high level of understanding and develop a decision support system to improve the quality of living of smart city decision support organizations.

2.8 Emerging Technologies

The development of innovative applications and the improvement of their performance for ubiquitous computing in smart city scenarios are getting a lot of attention from both academicians and industry. These areas bring together various exciting research challenges and opportunities for computer science researchers and practitioners. Here, we would like to highlight some of the most important emerging technologies that bring promising opportunities to the sustainable transformation of evolving smart city paradigms. Artificial intelligence and edge computing evolved as subsets of smart cities. Then, the advantages of integrating them are explained. A hybrid wireless network composed of mobile communication techniques could also be integrated into smart cities, for which the main cooperative approach for its enhancement of efficiency is cooperative vehicular networking. This and other related technologies are discussed.

Emerging Trends in Computing: Edge Computing and its Relationship with Smart Cities With the advent of 5G and the rapid development of IoT devices, cloud computing cannot meet the computing demand. For example, due to its low computing power, cloud computing cannot maximize the ability of IoT devices to continuously capture and transmit data, which is applicable to many identified systems in smart cities. Researchers and practitioners have proposed a paradigm shift from traditional cloud computing known as edge computing. Its objective is to move from centralized cloud environments to a distributed model, where data-intensive computation is performed by resource-constrained IoT devices closer to data sources with ultra-low latency. In edge computing, computation and data storage are still performed at the cloud, but the most frequently used data processing is performed on IoT devices or local servers.

2.9 Potential Impact on Smart Cities

Smart cities are initiatives involving governments and urban stakeholders to cultivate urban areas that are perceptive, connected, and sustainable. Modern technologies, especially communication and information technologies, are the most influential technologies used to render cities smarter. Concerning the dimensions of smart cities, it is intended to provide a holistic view of a city. As a double-edged sword, the data privacy and security challenges to AI-enhanced VANETs have to be faced with joint efforts from various sectors in the field of AI and VANETs. In conclusion, despite significant overhead in data privacy and security protection, AI-enhanced VANETs have a promising application in the smart cities transformation. In a smart city, the traffic management of the city is very important since the traffic system closely concerns the quality of life of the inhabitants and the operation of the social milieu. VANETs are critical to decrease visibility on the emission price and other social expenses of congestion in urban areas. AI-enhanced VANETs are also beneficial for the creation of open applications using clear and longstanding interfaces. The direct initial applications are Response Center and Vra for easy help in the event of an accident, and Driver Activity to objectively always estimate driver behavior and act on them. Dynamic data are planned to allow the composition of third-party traffic Vra, on-board devices to guide drivers directly in response to road traffic conditions.

3 Conclusion

Today, the smart cities transformation is a very much talked about research subject. Besides, a connected vehicle is a significant area of research pointing towards smart cities and transportation. With its huge potential in traffic safety, traffic efficiency, and environmental friendliness, and how these vehicles are moving towards the incorporation of advanced sensors and improved wireless connectivity, the media is calling the vehicle a smartphone on four wheels. As the vehicle has become sensing-enabled and computing-capable, a huge amount of data can be collected by vehicle sensors such as Limited Distance Communication, RADAR, cameras, and vehicle-to-infrastructure communications and vehicle-to-vehicle communications, which need to be processed at the vehicle and on the cloud. To drive all these required operational safety services, a reliable data offloading mechanism is necessary. This work discusses the enhancement of artificial intelligence techniques in conventional traffic management in order to further approach connected vehicle functionalities over the vehicular ad hoc networks. The AI-embedded environment could efficiently manage the increasing traffic. The congestion could be controlled, and warnings could be efficiently generated about events like accidents, bad roads, or any kind of traffic clogging conditions. Moreover, the AI-embedded physical environment could be integrated with traffic management infrastructure and equipped with traffic monitoring devices and traffic control devices. In conclusion, in this research work, various AI techniques of single and hybrid nature have been applied in the vehicular ad hoc networks area to develop smart cities with sensor-rich connected vehicles. These techniques have shown promising outcomes, depicting positive enhancements in terms of varying network-centric issues. It can therefore be concluded that future endeavors, enhancing new AI techniques in order to achieve network-centric and user-centric traffic management objectives, will lead towards the vehicle's complete transformation to connected vehicles that could solve several urban traffic problems burdening the world's smart cities.

3.1 Summary of Key Points

This study presented an AI-enhanced traffic management model that integrates AI techniques including Expert System, Artificial Neural Network, and Fuzzy Inference System into the framework of VANETs. It consists of three layers: perception, analysis, and response layers, where AI techniques are applied to enhance system intelligence. It applies to a shared memory-based approach to enable the queries and inferences on the shared knowledge that is utilized to increase traffic management intelligence. Vehicles arrive on the queries, receive answers and decisions from the shared memory, and can infer or display useful traffic information and predictions. All vehicles are able to obtain critical traffic information within a reasonable time and, most importantly, long before potential accidents take place. The solution approach can also be applied to other communication networks for other purposes to achieve specialized, ad-hoc communication network-based master–slave systems. The proposed solutions become stronger as the number of vehicles on the network increases. Overall, the proposed AI-enhanced traffic management model facilitates the transformation from conventional traffic management to AI-enhanced traffic management, from conventional VANETs to AI-enhanced VANETs, as well as from conventional cities to smart cities.

References

1. Ali, S., Khan, M.: Smart cities: Integrating IoT and AI for improved traffic management. J. Urban Technol. **28**(2), 123–145 (2021). https://doi.org/10.1080/10630732.2021.1894578
2. Chen, X., Zhang, J., Li, H.: The evolution of traffic management systems in smart cities: the role of AI and VANETs. Transp. Res. Part C: Emerg. Technol. **115**, 102614 (2020). https://doi.org/10.1016/j.trc.2020.102614
3. Dutta, S., Gupta, R.: AI-powered VANETs: revolutionizing traffic management in smart cities. IEEE Access **7**, 54179–54191 (2019). https://doi.org/10.1109/ACCESS.2019.2912728
4. Feng, C., Wang, Y.: Transitioning to smart traffic management: an AI and VANETs perspective. J. Intell. Transp. Syst. **26**(1), 57–72 (2022). https://doi.org/10.1080/15472450.2021.2001993
5. Huang, Y., Yang, L.: Artificial intelligence in VANETs: enhancing smart city traffic control. IEEE Trans. Intell. Transp. Syst. **21**(5), 2201–2212 (2020). https://doi.org/10.1109/TITS.2019.2934628
6. Jain, S., Kumar, A.: VANETs and AI in smart cities: a comprehensive review of traffic management. J. Traffic Transp. Eng. **8**(3), 274–286 (2021). https://doi.org/10.1016/j.jtte.2020.08.004
7. Kim, H., Lee, J.: Smart city traffic management through AI and VANETs integration. Sensors **19**(3), 678 (2019). https://doi.org/10.3390/s19030678

8. Liu, X., Zhao, Y.: The impact of AI-driven VANETs on urban traffic management systems. IEEE Commun. Surv. Tutorials **23**(4), 2267–2290 (2021). https://doi.org/10.1109/COMST.2021.3097931
9. Miller, T., Roberts, P.: From conventional traffic lights to AI-managed intersections: the role of VANETs. Transp. Res. Part A: Policy Pract. **155**, 267–282 (2022). https://doi.org/10.1016/j.tra.2021.11.015
10. Patel, R., Mehta, V.: AI-enhanced vehicular networks for traffic management in smart cities. Int. J. Commun. Syst. **33**(9), e4417 (2020). https://doi.org/10.1002/dac.4417
11. Ahmed, M., Khan, S., Ali, R.: Intelligent VANET architectures: leveraging ADAS and 5G for enhanced vehicular communication. IEEE Trans. Veh. Technol. **71**(5), 1234–1250 (2022)
12. Zhang, L., Wu, H.: Real-time data transmission in mobile VANETs: an ADAS-based approach. In: Proceedings of the International Conference on Smart Transportation Systems, pp. 87–99. IEEE (2021)
13. Singh, R., Sharma, K.: Leveraging AI in VANETs for smart city traffic solutions. Telecommun. Syst.. Syst. **78**(1), 59–72 (2021). https://doi.org/10.1007/s11235-021-00760-8
14. Tan, Q., Zhang, H.: Intelligent traffic systems in smart cities: the integration of AI and VANETs. IEEE Internet Things J. **9**(1), 603–615 (2022). https://doi.org/10.1109/JIOT.2021.3115401
15. Wang, M., Li, C.: Transforming traffic management in smart cities with AI and VANETs. Appl. Sci. **9**(21), 4625 (2019). https://doi.org/10.3390/app9214625
16. Smith, J.: Advances in vehicular networks: integrating ADAS with intelligent transportation systems. Springer (2020)
17. Zhou, X., Peng, Z.: AI-based VANETs for efficient traffic management in smart urban areas. J. Adv. Transp. **2020**, 8890132 (2020). https://doi.org/10.1155/2020/8890132
18. European Telecommunications Standards Institute (ETSI).: 5G-enabled vehicular networks and intelligent transport systems (Tech. Rep. No. ETSI TR 103 593 V1.1.1) (2021). https://www.etsi.org/technologies/5g-vehicular

AI and VANETs in Smart Cities: The Next Frontier in Traffic Management

Babasaheb Jadhav, Mudassar Sayyed, and Shashi Kant Gupta

Abstract The ever-increasing pace of urbanization and the increase in population have heightened the demand for innovative traffic management strategies aimed at ensuring sustainable mobility and alleviating congestion in smart cities. Conventional traffic management systems, which depend on fixed infrastructure and limited data integration, find it challenging to adapt to the ever-changing urban landscape. Hence, we need advanced technologies such as Vehicular Ad Hoc Networks (VANETs), which utilize vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication to facilitate real-time data exchange. The synergy of AI and VANETs represents a significant advancement. Advancement toward the development of intelligent traffic systems which can perform predictive analytics, make adaptive decisions, and optimize traffic flow seamlessly. Machine learning algorithms are used in AI-enhanced VANETs. This makes possible to process extensive real-time traffic data, allowing for precise predictions of traffic trends, prompt identification of incidents, and effective route planning. Additionally, this integration aids in the navigation of autonomous vehicles, coordination of emergency responses, and the reduction of carbon emissions through efficient energy management. This research looks at how AI can enhance Vehicle Ad Hoc Networks (VANETs) and transform urban transportation. It explores the potential benefits, such as improved efficiency and sustainability, while also addressing challenges like cybersecurity risks, infrastructure requirements and policy considerations. By integrating AI with VANETs, cities can create smarter and more connected transportation systems, shaping the future of urban mobility.

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1 Introduction

The transportation networks are currently under significant strain, and the fundamental reason is the rapid expansion of urban areas. This situation leads to traffic congestion, increased fuel consumption, and higher emissions. Conventional traffic management approaches, which depend on fixed infrastructure and predetermined controls, are inadequate for managing the dynamic and unpredictable characteristics of urban traffic. As cities make progress towards more intelligent and efficient mobility solutions, the integration of AI with VANETs offers a transformative opportunity for transportation systems. VANETs, which represent an innovative advancement in mobile ad hoc networking, provide new avenues for developing intelligent transportation systems [1]. In essence, these networks enable vehicles to function as independent communication nodes, interacting with each other and, when available, with roadside infrastructure. Unlike conventional networks that depend on fixed infrastructure, VANETs are inherently dynamic, forming temporary connections as vehicles move along roadways. With On-Board Units (OBUs), such vehicles can establish communication links dynamically which can form and terminate. This makes network topology highly fluid. Given that vehicles travel at different speeds and frequently enter and exit the network, maintaining seamless and efficient communication presents significant technical challenges. As illustrated in Fig. 1, the fundamental structure of VANETs is outlined by Kumar et al. [2].

Kumar et al. [2] introduced a structured framework for VANETs. They aimed at improving security and optimizing data transmission. The architecture proposed consists of three key layers': RSU Controllers, Zone Controllers, and a centralized certification authority.

The RSU Controllers manage multiple Roadside Units located at critical traffic points, while the Zone Controllers facilitate communication among various RSU Controllers. The CA is responsible for distributing cryptographic certificates and managing authentication processes. The hierarchical nature of this design is focused on enhancing data flow by ensuring that messages take a defined route and helps in reducing unnecessary transmissions. In this framework, vehicles send data to RSUs, which then pass the information to RSU Controllers, and if needed, to Zone Controllers. The CA is responsible for verifying digital certificates before allowing messages to be sent. Additionally, the model incorporates Elliptic Curve Cryptography for strong encryption and utilizes a sandboxing approach to address potential security risks in vehicle communications. Validation through simulations

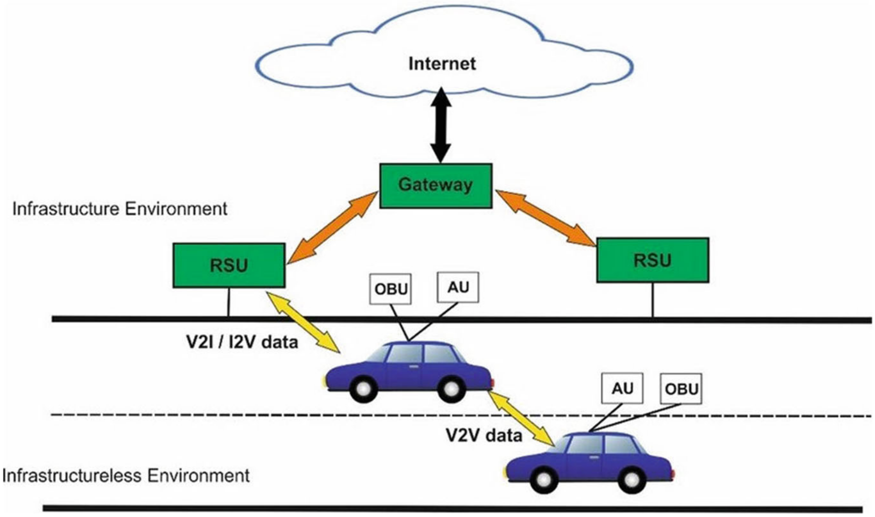

Fig. 1 Basic architecture of VANETs

demonstrates the architecture's effectiveness in lowering computational requirements, strengthening network security, and maintaining message integrity, even in the face of various cyberattack threats.

VANETs are dynamic and scalable. These networks can range from a limited group of vehicles operating on a secluded roadway to thousands of vehicles travelling on a busy highway. This dynamic nature necessitates the implementation of robust communication protocols and efficient resource management strategies. Furthermore, vehicles within these networks are generally equipped with GPS technology, which facilitates accurate geolocation tracking. This spatial awareness is vital for various VANET applications, such as optimized message routing and services tailored to specific locations. A significant impetus for the development of VANETs lies in their ability to improve road safety. The exchange of real-time data supports applications like collision avoidance alerts, emergency braking notifications, and cooperative awareness messages. These safety-oriented applications impose rigorous demands on the network, requiring low latency and high transmission reliability to avert accidents and enhance overall traffic management.

A conventional VANET architecture is made up of two main elements: one is On-Board Units located within vehicles and second is the Roadside Units strategically placed along transportation routes. Communication within such architectural framework occurs through various settings: V2V facilitates direct interactions among vehicles, V2I enables exchanges between vehicles and RSUs, and I2V allows for messages to be sent from RSUs to vehicles. This integration helps in creating a more flexible and responsive networking environment but there are many open challenges.

Some of the issues are efficient routing of messages in a dynamic setting, safeguarding communication pathways from potential threats, and handling the extensive data flow generated by expansive networks. Additionally, fulfilling the rigorous Quality of Service standards which are necessary for safety–critical applications adds another layer of complexity to network management. In response to these challenges, researchers are working on the development of novel routing protocols, improved security frameworks, and adaptive management techniques. The future advancement of VANET technology is dependent on addressing these challenges.

VANETs facilitate uninterrupted communication between vehicles and roadside infrastructure, enabling the real-time exchange of data that enhances traffic management, increases safety, and optimizes routing. Nevertheless, traditional implementations of VANETs encounter considerable challenges, such as vulnerabilities to cybersecurity threats, delays in decision-making processes, and issues related to scalability in extensive and varied urban environments. To tackle such challenges what we need is a sophisticated AI-driven framework. Such frameworks should be able to incorporate decentralized learning methods, secure communication protocols, and adaptive algorithms for decision-making.

This chapter investigates the core design principles, operational mechanisms, and practical implications of AI-augmented VANETs, providing a detailed framework for the integration of intelligent transportation systems in urban areas. Here we analyze various components of an AI-centric vehicular network, emphasizing the importance of perception in collecting real-time data, the network infrastructure that supports effective communication, and the decision-making processes that enable smart mobility solutions. Later on, the chapter addresses the cybersecurity risks in implementing AI in VANETs and discusses strategies to maintain data integrity, privacy, and resilience against cyber threats.

This chapter also presents a methodology for performance evaluation. We propose simulation-based assessments, mathematical modeling, and real-world pilot studies. By creating a comprehensive framework that enhances urban mobility through automation and predictive analytics, AI-driven VANETs contribute to the development of safer, more efficient, and environmentally friendly transportation systems.

2 AI-Driven Vehicular Network Architecture

The effectiveness of intelligent transportation systems is strictly dependent on a robust and flexible communication framework that facilitates the efficient exchange of information between vehicles and infrastructure. A well-designed architecture serves as the cornerstone for real-time data acquisition, uninterrupted connectivity, and autonomous decision-making processes. In contrast to conventional traffic management methods that rely on predetermined signal timings and fixed congestion models, AI-enhanced VANETs utilize real-time data sourced from vehicles, infrastructure, and cloud computing to establish a dynamic and intelligent mobility network

[3]. In this section we present three essential layers of the system: the Perception Layer, Network Layer, and Decision-Making Layer. The perception layer collects and processes environmental data. The network layer ensures dependable communication between mobile entities and infrastructure and the decision-making layer is where the AI-based models evaluate information and formulate optimal traffic management strategies.

2.1 Perception Layer

The capacity to analyze real-time road conditions is fundamental to any sophisticated transportation system. The perception layer functions as the system's sensory apparatus, gathering data from various sources and verifying its accuracy prior to forwarding it to higher processing tiers. Vehicles have many sensors, such as LiDAR, radar, GPS, and high-resolution cameras, which together create a comprehensive representation of the surrounding environment. These technologies collaborate to identify obstacles, gauge distances, monitor movement patterns, and evaluate overall road conditions [4].

However, despite their individual capabilities, sensors are not infallible. For instance, visual cameras may encounter difficulties in low-light situations or during heavy precipitation, while LiDAR may struggle in environments with high reflectivity. To address these limitations, sensor fusion techniques amalgamate data from various sources, thereby enhancing the reliability of the information gathered. This improved dataset facilitates real-time hazard detection, adaptive cruise control, and more effective lane navigation, ultimately decreasing the likelihood of accidents.

In addition to the sensors mounted on vehicles, roadside units provide an external viewpoint to the perception framework. These strategically positioned devices gather extensive traffic data, including congestion levels, signal timings, and pedestrian movement patterns. The integration of RSUs with IoT infrastructure bolsters overall situational awareness, ensuring that vehicles receive precise and timely information. Processing such a vast amount of data in real time presents significant computational challenges, which is why edge computing is essential at this stage. Rather than depending solely on cloud-based processing, AI models are incorporated within the perception layer to filter and preprocess data before it is transmitted. By decreasing the reliance on extensive cloud communication, edge computing reduces latency, improves system responsiveness, and guarantees that time-sensitive decisions, such as emergency maneuvers, can be made effectively [5].

2.2 Network Layer

Once environmental data is collected, it is imperative that it be transmitted swiftly and securely throughout the system to enable coordinated decision-making. The network layer facilitates this transmission by creating dependable communication pathways among vehicles, roadside infrastructure, and cloud-based control centers. To ensure seamless operation, the communication framework must effectively manage substantial data volumes, reduce latency, and safeguard against unauthorized access.

The communication infrastructure functions via direct V2V communication and V2I interaction. In V2V communication, moving vehicles exchange real-time information regarding their location, speed, and routes. Effective communication between vehicles makes it possible for vehicles to collaborate driving techniques and aids in the proactive prevention of collisions. In contrast, V2I communication provides vital information regarding traffic control signals, updates on navigation, and notifications concerning potential road hazards. The amalgamation of these two communication modalities cultivates a responsive network where vehicles are equipped to react to their current surroundings while also forecasting upcoming traffic scenarios. The communication framework of Vehicular Ad Hoc Networks is depicted in Fig. 2 [6].

The issue of ensuring secure, low-latency communication presents a considerable barrier to unlocking the full capabilities of interconnected vehicular systems. Conventional centralized computing frameworks frequently fall short of meeting the requirements for high-speed vehicle interactions, which demand responses within milliseconds. A more effective strategy involves the adoption of distributed networking models. Such models utilize edge computing nodes in conjunction with 5G cellular

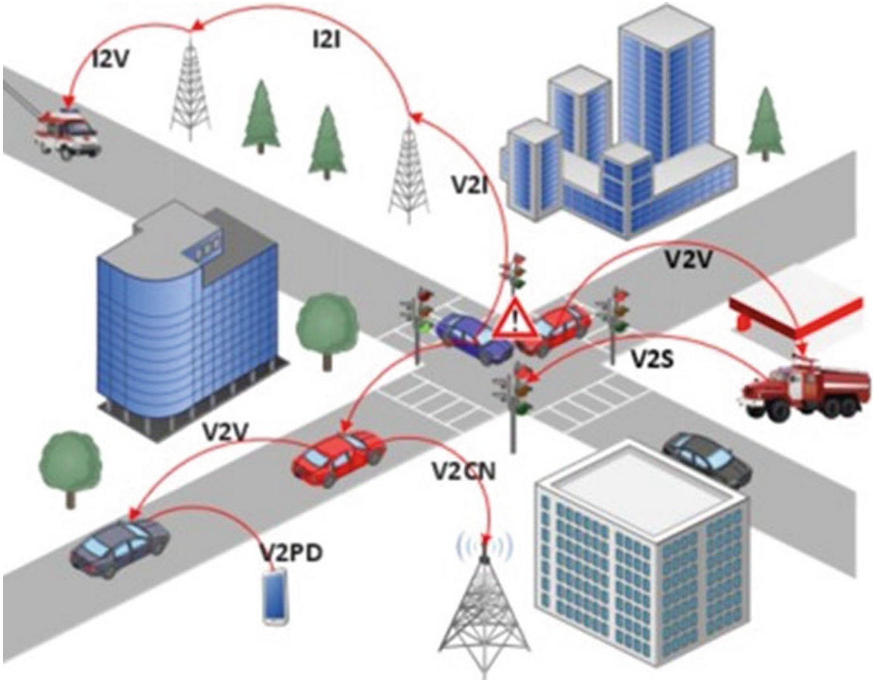

Fig. 2 Communication architecture of VANETs

technology. This approach facilitates real-time communication by enabling vehicles to engage directly with nearby processing units, thus reducing dependence on extensive data transmission and promoting swift decision-making.

Security is a critical concern in any interconnected framework, especially in transportation infrastructure, where potential vulnerabilities could be exploited to cause significant disruptions. To mitigate security risks, sophisticated encryption protocols and blockchain-based authentication systems are implemented. The use of blockchain technology guarantees the verification and permanence of data transactions, effectively thwarting unauthorized alterations to essential traffic information. Additionally, AI-driven anomaly detection systems are employed to continuously analyze communication patterns, allowing for the early identification and resolution of potential security threats before they can jeopardize network integrity.

2.3 Decision-Making Layer

At the core of an advanced vehicular system is its capacity for self-decision-making. This component analyzes real-time data, forecasts future traffic patterns, and optimizes the route selection to improve urban mobility. By utilizing machine learning and reinforcement learning methodologies, artificial intelligence algorithms consistently enhance their decision-making capabilities, thereby promoting efficiency and adaptability.

A prominent application of AI in this domain is the optimization of traffic flow. Conventional traffic signal management typically depends on fixed timing schedules that do not respond to actual congestion levels. In contrast, AI-based models evaluate real-time vehicle density, historical data, and predictive analytics to dynamically adjust signal timings, thereby minimizing wait times and increasing traffic throughput. Another critical role of this decision-making layer is autonomous route selection. Vehicles equipped with sophisticated navigation systems evaluate various route alternatives based on current conditions, optimizing travel routes to alleviate congestion and reduce fuel consumption. These algorithms consider elements such as accident reports, road construction updates, and weather conditions to make well-informed decisions that benefit both individual drivers and the overall traffic ecosystem.

Cooperative decision-making is significantly advanced through the application of Multi-Agent Reinforcement Learning (MARL), wherein multiple AI-enabled vehicles work in concert to enhance mobility. By exchanging information and learning from one another's behaviors, these autonomous agents formulate traffic management strategies that are both effective and scalable. MARL facilitates coordinated lane changes, adaptive merging techniques, and smart intersection management. Such capability is helpful in alleviating congestion and enhancing overall road safety.

Although AI is important in automating traffic-related decisions, human oversight is essential to ensure adherence to ethical standards and regulatory requirements. If any unpredictable pattern emerges such as novel road conditions, human operators are crucial for providing necessary interventions. This hybrid approach to decision-making harmonizes automation with accountability, prioritizing safety and efficiency [7].

As transportation systems advances, the decision-making framework will have to engage increasingly sophisticated deep learning models. Such integration will allow for enhanced precision and adaptability. The collaboration between AI, real-time data, and secure networking infrastructures will propel the future of intelligent mobility, transforming urban transportation into a highly efficient, safe, and interconnected system.

3 Cybersecurity in AI-Enhanced Vehicular Networks

In digital and interconnected transportation systems, cybersecurity is very important. The dependence on real-time data sharing and artificial intelligence for decision-making creates substantial vulnerabilities, positioning vehicular networks as attractive targets for cyber threats. It is crucial to ensure the security and integrity of communications to uphold public confidence, avert malicious attacks, and protect the reliability of autonomous mobility solutions. This section examines the principal security challenges, and the strategies required to defend intelligent transportation networks against the evolving landscape of cyber risks. Figure 3 illustrates the various methods through which attackers can disrupt vehicular communication maliciously [8]. The authors highlight the cyber vulnerabilities inherent in a vehicular ecosystem.

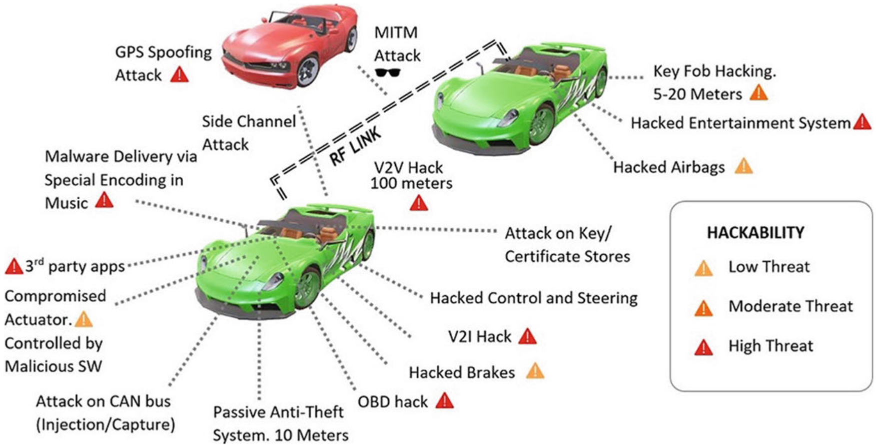
GPS Spoofing Attack ⚠
MITM Attack
Key Fob Hacking. 5-20 Meters ⚠
Hacked Entertainment System ⚠
Hacked Airbags ⚠
Side Channel Attack
RF LINK
Malware Delivery via Special Encoding in Music ⚠
V2V Hack 100 meters ⚠
⚠ 3rd party apps
Attack on Key/ Certificate Stores
Compromised Actuator. ⚠ Controlled by Malicious SW
Hacked Control and Steering
V2I Hack ⚠
Hacked Brakes ⚠
Attack on CAN bus (Injection/Capture)
Passive Anti-Theft System. 10 Meters
OBD hack ⚠
HACKABILITY
⚠ Low Threat
⚠ Moderate Threat
⚠ High Threat

Fig. 3 Cyber vulnerabilities in a vehicular ecosystem

3.1 Protecting Communication Integrity and Data Authenticity

Data is central to the AI-driven vehicular ecosystem. It flows to and from mobile entities, roadside infrastructure, and cloud-based servers. The precision and reliability of this data are critical for ensuring traffic safety and managing congestion effectively. Nonetheless, communication networks are vulnerable to various types of cyber threats, such as data spoofing, man-in-the-middle attacks, and unauthorized access.

A significant concern is the falsification of messages, wherein an attacker introduces erroneous data into the system. For example, a compromised vehicle might disseminate false congestion notifications, misleading AI-driven routing systems into unnecessarily redirecting traffic. Such disturbances not only lead to operational inefficiencies but can also be manipulated for more severe attacks, including rerouting emergency services or instigating traffic jams in key locations. To mitigate these risks, cryptographic authentication methods are essential. Digital signatures and Public Key Infrastructure ensure that only authenticated sources are permitted to send data within the network. Each communication between vehicles and infrastructure is digitally signed, enabling recipients to confirm its authenticity prior to acting. Furthermore, the integration of blockchain technology enhances communication security by establishing an immutable ledger that records and verifies all interactions. As blockchain functions on a decentralized consensus model, it removes single points of failure, thereby increasing resilience against cyber threats.

3.2 Defending Against Unauthorized Access and System Breaches

As vehicular networks increasingly depend on artificial intelligence and cloud-based control systems, the potential for unauthorized access to vital components escalates considerably. Should cybercriminals seize control of critical functions such as braking, acceleration, or navigation they could alter vehicle operations, posing risks to both passengers and pedestrians. Additionally, widespread security breaches could severely impact entire traffic management infrastructures, resulting in disorder on public roadways.

A crucial strategy for safeguarding against unauthorized access is to implement AI-driven Intrusion Detection Systems. These systems provide real-time monitoring of vehicular communications, detecting patterns that may signify impending attacks. In contrast to conventional security measures that depend on established rules, AI-enhanced IDS adaptively learn from emerging threats, enabling them to recognize even novel attack methodologies. Upon identifying anomalies, the system can isolate compromised nodes, thereby curtailing the further dissemination of malicious activities.

One additional effective strategy involves the adoption of end-to-end encryption for all communication channels. This encryption of data guarantees that even if an adversary manages to intercept messages, they will not be able to interpret the information without the appropriate cryptographic keys. The implementation of robust key management protocols further enhances this strategy, ensuring that encryption credentials are safeguarded against unauthorized access.

In addition to technological safeguards, regulatory frameworks are crucial in ensuring the security of autonomous transportation systems. It is imperative for governments and industry organizations to develop rigorous cybersecurity standards that require regular security audits, vulnerability assessments, and adherence to established encryption protocols. By enforcing these cybersecurity best practices, policymakers can foster a more secure environment in which AI-driven transportation can function with reduced risk of compromise.

3.3 Addressing Real-Time Security Challenges in High-Speed Mobility

One of the distinct challenges in safeguarding vehicular networks is the requirement for immediate protection in a dynamic mobility setting. In contrast to conventional networks, where security protocols can tolerate minor delays, intelligent transportation systems function under strict time limitations. Any security solution should guarantee that such protective actions do not introduce latency, as this could interfere with traffic management and emergency responses.

AI-powered cybersecurity frameworks offer a robust solution by facilitating predictive threat detection. Rather than merely responding to attacks post-occurrence, AI-based security models can predict vulnerabilities by analyzing historical data and emerging cyber threats. Through the examination of communication logs and network activities, machine learning algorithms pinpoint system weaknesses, enabling proactive measures to be taken before potential breaches arise. A vital component of real-time security is the ability to distinguish between authentic system malfunctions and deliberate cyberattacks. For instance, a sudden loss of connection between a vehicle and an infrastructure node could be due to natural signal disruptions or a targeted denial-of-service attack. AI models that are trained on a wide range of datasets play a key role in accurately identifying these events, ensuring that security responses are tailored to genuine threats while reducing the likelihood of false alarms.

To further bolster real-time security, vehicular networks employ decentralized authentication methods. Instead of depending on a single verification authority, these systems distribute trust across multiple nodes, making it difficult for attackers to target a central control point. This decentralized strategy not only enhances security but also meets the scalability requirements of modern smart transportation systems.

3.4 Privacy Protection and Ethical Considerations

In today's world, where data privacy is important, smart vehicle networks need to make user information protection a top priority. Cars are constantly collecting tons of data, like where they've been, how they're driven, and personal details. If this data isn't properly secured, it could be misused for things like unauthorized tracking, identity theft, or cyberattacks. One way to keep privacy intact is by using anonymization techniques. By removing or masking personal identifiers from the data they send out. In this way vehicles can help with traffic management without revealing sensitive info. Plus, AI-powered privacy algorithms can make sure that this anonymization doesn't mess with the accuracy needed for real-time decisions.

But it's not just about the tech; ethical factors also need to be part of how we design AI in transportation. Being clear about data collection practices, having user consent processes, and establishing accountability are all crucial for building public trust. As self-driving technology advances, aligning cybersecurity with ethical standards will be key to getting people on board with these innovations.

Ensuring the security of AI-driven transportation systems is not merely a technical obligation; it is a crucial aspect of public safety and trust. This involves securing communication channels, preventing unauthorized access, addressing real-time cyber threats, and safeguarding user privacy through multiple layers of defense within vehicular networks. The integration of AI-enhanced threat detection, robust encryption protocols, and decentralized authentication frameworks establishes a solid foundation for risk mitigation in this dynamic environment.

As cyber threats continue to advance, security measures must also adapt to protect intelligent transportation systems. Ongoing research, practical testing, and collaboration among industry stakeholders are vital for sustaining resilient, trustworthy, and future-ready vehicular communication networks. By proactively tackling these challenges, AI-driven mobility systems can function with assurance, paving the way for a safer and more efficient transportation landscape.

4 Performance Evaluation and Validation

For the successful integration of intelligent vehicular systems into practical applications, comprehensive validation is crucial to guarantee their reliability, efficiency, and security. AI-enhanced transportation networks need to undergo testing across a variety of conditions to evaluate their responsiveness to traffic variations, environmental obstacles, and cybersecurity risks. An effective evaluation framework encompasses several testing phases, ranging from simulations and mathematical modeling to actual deployment in real-world scenarios. This section delves into the methodologies employed to validate AI-based vehicular networks, confirming their resilience prior to widespread adoption.

4.1 Simulation-Based Testing in Smart Mobility Systems

Simulations are essential for evaluating how well AI-based traffic networks work, avoiding the risks and expenses of real-world implementation. By mimicking actual traffic situations in a controlled digital space, researchers can study how AI systems react to issues like traffic jams, accidents, weather changes, and unexpected roadblocks. These virtual environments allow for ongoing adjustments, where algorithms can be improved based on their performance before moving to real-world tests.

One popular tool for traffic simulation is the Simulation of Urban Mobility (SUMO), which is open-source and supports large-scale transportation modeling. SUMO allows for testing AI-driven route planning, traffic light management, and emergency response strategies. By using real-time vehicle movement data, these simulations assess important performance indicators such as average travel time, congestion reduction, and energy use. Additionally, network simulators like NS-3 evaluate the reliability of vehicle communication, ensuring that data is sent quickly and accurately [9]. One key benefit of simulation-based validation is the chance to study how systems perform in extreme situations that are hard or unsafe to test in real life. For example, researchers can see how AI models respond to large cyberattacks, unexpected infrastructure breakdowns, or multiple vehicle accidents. This method helps ensure that the system stays strong even in risky situations.

Additionally, digital twins, which are virtual copies of real transportation systems, provide a sophisticated way to assess AI-powered traffic management. By linking simulation models with real-time data from cities, researchers can improve decision-making based on current road conditions. This ongoing feedback enhances the flexibility of AI algorithms, making sure they work well in different traffic scenarios and locations.

4.2 Mathematical Modeling for System Optimization

Mathematical models extend beyond mere simulations, offering a theoretical foundation for the validation of AI-driven vehicular networks. These models facilitate the establishment of formal proofs regarding system behavior, enabling researchers to anticipate the performance of AI algorithms across various constraints. By articulating transportation dynamics through established mathematical principles, researchers can optimize strategies prior to their application in practical scenarios.

A prominent method employed in this context is the Markov Decision Process (MDP), which effectively represents decision-making in environments characterized by uncertainty. Given that AI-enhanced traffic systems are in a constant state of adaptation to fluctuating road conditions, MDPs are instrumental in examining how autonomous agents, such as self-driving cars, determine optimal routes while simultaneously reducing congestion and travel duration. The reinforcement learning algorithms that underpin these decisions are based on state transitions, where each alteration in traffic conditions impacts subsequent choices [10]. By resolving MDPs, researchers can identify the most effective navigation policies within the constraints of real-world scenarios [11].

An additional significant mathematical instrument is Partial Differential Equations (PDEs), which characterize the dynamics of large-scale traffic flow. The Lighthill–Whitham–Richards (LWR) model serves as a foundational framework for understanding the variations in vehicular density across both time and space [12]. By combining PDE-based models with artificial intelligence-driven traffic optimization, researchers can assess the effects of intelligent signal coordination on congestion and overall throughput efficiency.

Game theory is important for understanding how self-driving cars and human-driven vehicles interact. Traffic systems act like multi-agent systems, where each driver or AI makes choices that affect overall traffic flow. Game-theoretic models, like Nash equilibrium, help predict how vehicles will either compete or work together when choosing routes, merging lanes, or responding to unexpected road situations. It’s essential for AI models to match stable traffic patterns to avoid chaotic or aggressive driving.

Queuing theory also looks at how efficiently data is transmitted in vehicle communication networks. Intelligent transportation systems depend on quick message exchanges, and delays can hurt decision-making. By treating data packet transmission as a queuing process, researchers can improve message scheduling, reduce delays, and make AI-driven mobility solutions more responsive.

With mathematical validation, AI-based transportation networks get a solid theoretical basis that supports real-world testing. These models not only show that AI decision-making is possible but also help designers improve performance before full deployment.

4.3 Real-World Deployment and Testing

Simulations and mathematical models offer useful insights, but they can’t completely mimic the complexity of real traffic situations. To test how well AI-driven vehicle networks work in busy urban areas, it’s important to deploy them in real life. Pilot projects and controlled test areas help researchers and city planners evaluate how these systems perform in real driving conditions, taking into account unpredictable human actions, infrastructure challenges, and outside environmental factors.

A main goal of real-world deployment is to see how well AI mobility systems work with current transportation infrastructure. Intelligent roadside units, adaptive traffic signals, and coordination of autonomous vehicles need to operate smoothly with traditional vehicles and manual traffic controls. To do this, phased deployment strategies are often used, where AI traffic management is gradually introduced in specific test zones. These zones are closely observed to measure important performance indicators, like improving traffic flow, response times in emergencies, and the system’s ability to manage rush hour congestion.

Smart city projects have created great testing grounds for checking out AI-powered vehicle networks. Cities like Singapore and some areas in Europe have rolled out AI-based traffic management systems that use connected cars and smart road sensors to fine-tune traffic signals and vehicle routes. These initiatives show how AI can help make travel quicker, boost fuel efficiency, and cut down on emissions. However, one of the main hurdles in real-world testing is making sure vehicles and infrastructure stay connected smoothly. Unlike controlled tests, real-life situations come with issues like signal disruptions, GPS errors, and changing network conditions. To tackle these problems, AI vehicle networks use a mix of edge computing and 5G tech, which allows for quick data processing at local points while keeping cloud coordination for long-term predictions.

Besides just testing performance, real-world trials are essential for meeting regulations and gaining public trust. Transportation agencies need to make sure that AI-driven decisions follow traffic laws and safety guidelines. Plus, how the public feels about these smart transport solutions is super important for their acceptance. Testing with both self-driving and human-driven cars helps policymakers gauge driver confidence, system ease of use, and how well AI safety features work. Real-world deployments provide valuable insights that help fine-tune AI models, boost adaptive learning skills, and tackle unexpected technical challenges. By carefully studying how these systems perform in actual traffic situations, researchers can make them more reliable, setting the stage for a complete integration of smart transportation solutions.

4.4 Cybersecurity Resilience Testing

The integration of AI-driven vehicular networks, which manage extensive volumes of real-time data, necessitates a strong focus on cybersecurity to mitigate potential cyber threats. Conducting resilience testing for cybersecurity is essential to safeguard vehicular communication from unauthorized access, data tampering, and network interruptions. In contrast to conventional IT systems, which can tolerate slight delays in security protocols, intelligent transportation networks must adhere to strict real-time operational requirements [13]. Any interruption in data flow or decision-making processes poses significant safety hazards, underscoring the importance of proactive security assessments.

Penetration testing stands out as a highly effective method for uncovering vulnerabilities within vehicular networks. Ethical hackers engage in simulated cyberattacks to test the integrity of AI-based traffic management systems, intercept vehicular communications, or take advantage of inadequate authentication measures. These controlled scenarios enable developers to fortify security infrastructures, rectify vulnerabilities, and establish multi-layered defense strategies. Additionally, red-teaming exercises, where cybersecurity professionals rigorously test AI-enhanced security systems in a competitive setting, further bolster resilience by ensuring that security measures can withstand evolving threats.

Artificial intelligence is essential for spotting and reducing cyber threats in vehicle networks. AI-based Intrusion Detection Systems (IDS) keep an eye on network traffic, looking for patterns that might show an attack. Unlike older security methods that depend on fixed threat models, machine learning-based IDS can quickly adjust to new attack methods. These systems check vehicle communications for unusual behavior, marking suspicious actions and stopping unauthorized data changes.

Another important cybersecurity step is using blockchain technology to protect data exchanges. By using a decentralized ledger, vehicle networks can stop bad actors from changing important information like navigation updates, traffic alerts, or accident reports. The cryptographic security of blockchain makes sure that all messages sent in the network are secure from tampering, lowering the chances of data spoofing or unauthorized message insertion. End-to-end encryption enhances cybersecurity by keeping communication between vehicles and infrastructure private. If an attacker tries to intercept data, encryption makes the message unreadable without the right cryptographic key. Secure key management systems stop unauthorized access to these keys, allowing only trusted parties to engage in vehicle communication.

A significant challenge in testing cybersecurity resilience is protecting against attacks from adversarial AI. Malicious individuals may try to trick AI models by providing altered data, leading to wrong predictions or errors in route planning. To address these threats, AI models are trained with adversarial learning methods, where they learn from misleading inputs during training. This approach improves the model's strength, ensuring that AI decision-making stays reliable even when facing advanced cyber threats.

Cybersecurity resilience testing is crucial for assessing how quickly systems can respond during an attack. In environments where mobility is key, the ability to swiftly detect and address threats becomes vital. Security frameworks powered by AI are specifically designed to implement automated containment strategies, which help isolate affected network nodes and redirect traffic away from compromised areas. By continuously improving their cybersecurity response plans, vehicular networks can lessen the effects of cyberattacks while ensuring they operate smoothly.

As AI-enhanced transportation systems advance, their cybersecurity measures must also progress. Ongoing research, collaboration between cybersecurity professionals and transportation engineers, and the adoption of sophisticated encryption methods will be vital in safeguarding vehicular networks from new cyber threats. The effectiveness of intelligent transportation systems relies not only on managing traffic efficiently but also on creating a trustworthy environment that emphasizes safety, privacy, and resilience against potential threats.

5 Conclusion

The evolution of AI-driven vehicular networks represents a remarkable shift in contemporary transportation, offering the potential for safer, more efficient, and highly adaptable mobility solutions. This chapter delved into the key elements of intelligent vehicular communication systems, emphasizing architecture, cybersecurity, performance validation, and practical implementation. The incorporation of artificial intelligence has transformed the way vehicles communicate with one another and with their surrounding infrastructure, enhancing decision-making processes and boosting overall traffic efficiency.

At the core of these networks is their architecture, which consists of three interconnected layers: the Perception Layer, the Network Layer, and the Decision-Making Layer. The Perception Layer is responsible for accurately collecting real-time data from various sources, such as onboard sensors and roadside infrastructure, while edge computing processes this data to reduce latency. The Network Layer enables smooth communication, allowing vehicles to share vital information in real time, all while utilizing secure encryption methods to protect against cyber threats. Finally, the Decision-Making Layer, driven by AI algorithms, optimizes routing, traffic management, and congestion control, ensuring that both autonomous and human-driven vehicles function effectively within smart city settings.

A key part of AI-based vehicle systems is cybersecurity, which defends against a growing number of cyber threats. The safety of vehicle communication relies on cryptographic authentication, intrusion detection systems, and blockchain verification. AI security frameworks keep an eye on network activity to spot unusual behavior, stopping unauthorized access and data tampering. These protective measures are vital for maintaining the integrity of vehicle networks and making sure they can resist potential cyberattacks. Privacy is also important, as it is necessary to safeguard sensitive information about vehicles and drivers from unauthorized access or misuse.

To ensure these systems perform well and are secure, thorough testing methods are used. Simulation testing helps researchers create real-world traffic scenarios to improve AI algorithms before they are fully implemented. Mathematical modeling gives a theoretical basis, making sure AI decisions follow established traffic rules. Real-world testing provides insights into how these smart systems work with current transportation setups, highlighting issues that need to be resolved before widespread use. Additionally, testing for cybersecurity resilience is crucial to evaluate how well the system can handle cyber threats, ensuring that encrypted communication, decentralized authentication, and AI anomaly detection function properly in real-life situations.

As AI-driven vehicular communication systems gain traction, ongoing research and innovation will be essential to enhance these technologies. The incorporation of cutting-edge advancements like 6G connectivity, quantum-safe cryptography, and decentralized AI learning frameworks will be crucial for improving the scalability and security of smart transportation networks. Additionally, future initiatives must tackle ethical issues, regulatory guidelines, and public acceptance to ensure that AI-based mobility solutions meet societal demands and safety requirements.

In summary, AI-enhanced vehicular communication networks hold the promise to transform urban transportation by alleviating congestion, boosting road safety, and increasing overall efficiency. Nevertheless, the effectiveness of these systems hinges on persistent progress in AI, cybersecurity, and network optimization. By overcoming technical hurdles and implementing thorough validation processes, AI-driven transportation can lead to a more intelligent, secure, and interconnected mobility landscape.

References

1. Kanellopoulos, D., Cuomo, F.: Recent developments on mobile ad-hoc networks and vehicular ad-hoc networks. Electronics **10**(4), Article 4 (2021). https://doi.org/10.3390/electronics10040364
2. Kumar, G., et al.: Multidimensional security provision for secure communication in vehicular ad hoc networks using hierarchical structure and end-to-end authentication. IEEE Access. 1–1 (2018). https://doi.org/10.1109/ACCESS.2018.2866759
3. Alhilal, A.Y., Finley, B., Braud, T., Su, D., Hui, P.: Street smart in 5G: vehicular applications, communication, and computing. IEEE Access **10**, 105631–105656 (2022). https://doi.org/10.1109/ACCESS.2022.3210985
4. Sadaf, M., et al.: Connected and automated vehicles: infrastructure, applications, security, critical challenges, and future aspects. Technologies **11**(5), Article 5 (2023). https://doi.org/10.3390/technologies11050117
5. Khalil, R.A., Safelnasr, Z., Yemane, N., Kedir, M., Shafiqurrahman, A., Saeed, N.: Advanced learning technologies for intelligent transportation systems: prospects and challenges. IEEE Open J. Veh. Technol. **5**, 397–427 (2024). https://doi.org/10.1109/OJVT.2024.3369691
6. Mchergui, A., Moulahi, T., Zeadally, S.: Survey on artificial intelligence (AI) techniques for vehicular ad-hoc networks (VANETs). Veh. Commun. **34**, 100403 (2022). https://doi.org/10.1016/j.vehcom.2021.100403
7. Ning, Z., Xie, L.: A survey on multi-agent reinforcement learning and its application. J. Autom. Intell. **3**(2), 73–91 (2024). https://doi.org/10.1016/j.jai.2024.02.003
8. El-Rewini, Z., Sadatsharan, K., Selvaraj, D.F., Plathottam, S.J., Ranganathan, P.: Cybersecurity challenges in vehicular communications. Veh. Commun. **23**, 100214 (2020). https://doi.org/10.1016/j.vehcom.2019.100214
9. Campanile, L., Gribaudo, M., Iacono, M., Marulli, F., Mastroianni, M.: Computer network simulation with ns-3: a systematic literature review. Electronics **9**, 272 (2020). https://doi.org/10.3390/electronics9020272
10. Garcia, F., Rachelson, E.: Markov decision processes. In: Markov Decision Processes in Artificial Intelligence: MDPs, Beyond MDPs and Applications, pp. 1–38 (2013). https://doi.org/10.1002/9781118557426.ch1
11. Inamdar, R., Sundar, S.K., Khandelwal, D., Sahu, V.D., Katal, N.: A comprehensive review on safe reinforcement learning for autonomous vehicle control in dynamic environments. E-Prime—Adv. Electr. Eng. Electron. Energy **10**, 100810 (2024). https://doi.org/10.1016/j.prime.2024.100810
12. Mazaré, P.-E., Dehwah, A.H., Claudel, C.G., Bayen, A.M.: Analytical and grid-free solutions to the Lighthill Whitham Richards traffic flow model. Transp. Res. Part B: Methodol. **45**(10), 1727–1748 (2011). https://doi.org/10.1016/j.trb.2011.07.004
13. Durlik, I., Miller, T., Kostecka, E., Zwierzewicz, Z., Łobodzińska, A.: Cybersecurity in autonomous vehicles—are we ready for the challenge? Electronics **13**(13), Article 13 (2024). https://doi.org/10.3390/electronics13132654

Next-Generation VANETs: Deep Learning, Machine Learning, and Secure AI Integration for Real-Time Urban Mobility

Fawad Ullah and Muhammad Ameer Hamza

Abstract As vehicle ad hoc networks (VANETs) grow rapidly, AI is essential to the breakthrough advancements in intelligent transportation systems. Traffic control using deep learning (DL) and machine learning (ML) algorithms and self-organized decision-making in VANETs has been made possible by the rapid development of autonomous and connected cars and the rising need for road safety. An ideal traffic flow and risk awareness mode were achieved with a variety of machine learning approaches, including support vector machines, random forests, and reinforcement learning. However, DL models give smart-based collision estimates as well as enhanced techniques to assist an aircraft in avoiding collisions. Convolutional Neural Networks (CNNs) are these models. RNNs and LSTMs are two examples. However, there are still problems with privacy, real-time processing, and data diversity. Preparing networked, connected car systems with contemporary technologies like edge computing, federated learning, and adversarial robustness to make VANET systems scalable and safe is one of the next challenges. Digital twin models, collaborative AI, and fifth-generation, or 5G, connectivity are examples of new technologies that promise to advance VANETs by enhancing their environmental, security, and adaptability. This chapter highlights the prospective directions that have not yet been investigated and gives a summary of the current AI tools and issues in VANET. AI-powered VANETs can revolutionize the current transportation ecosystem and provide the most sophisticated and intelligent solution to the challenges it faces. To meet the demands of the constantly connected and urban environment, they can also offer safer transportation.

Keywords VANETs (Vehicular Ad-hoc Networks) · Machine learning · Deep learning · Real-time processing

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1 Introduction

With the speed at which it has been incorporated into the transporting system with intelligence in the transport system, VANETs, and AI. Therefore, incorporating Deep Learning (DL) and Machine Learning (ML) technologies into these networks enables data to be analyzed in real-time and able to make decisions and take actions accordingly, enhancing traffic flow and road safety [1]. However, these lies have negative implications. Therefore, several challenges make it difficult to deploy AI in VANETs, such as data Multidimensionality, the need for Real-time processing, Restricted Resources, Security threats, and non-interpretable deep learning models. To get proper coverage and to facilitate the fulfillment of the AI-integrated VANET to its maximum [2].

In particular, in the case of the arrival of DL and ML, the most prominent ones appeared, VANETs. Self-drive's availability in Android OS is feasible. It can be utilized in collision-free and automated operations due to the advancement in the number of objects in every automobile and their surroundings [3]. Innovations such as federated learning, edge AI, and graph neural networks are proposed for some of the challenges imposed by VANET; they serve as the basis for dealing with intelligent VANET, which has improved scalability, security, and real-time operation. Due to 5G and explainable AI (XAI), the trendy way for ultra-modern mobility with safety, efficacy, and dependableness is waiting.

However, several upcoming new trends can be ascribed to AI's ability to enhance VANETs. ITS architectures were envisioned to transform into advanced concepts, an open-ended list to mention but a few—cooperative AI, digital twins, sustainability-oriented models, etc. [4]. New communication technologies can be used, and the AI algorithms can be improved to achieve better sustainability, security, and performance of the VANETs. These future roads are the solution to these existing problems; however, these roads can be used to solve road safety and traffic problems at an unknown level in these complex urban environments [5].

1.1 Vehicular Ad-Hoc Network

This can be used as an entertainment system and to enhance traffic control and road safety through the Mobile Ad hoc (MANET) framework. This is the first kind of network that enables a car to talk to other cars and roadside equipment organized during traffic, as seen in Fig. 1. On-road side and application units are the three primary categories of the network's communication interfaces [6].

- **On-Board Unit (OBU)**: Every car uses this gadget. After receiving data, it sends it to other RSUs or OBUs.
- **Application Unit (AU)**: Information from OBU is sent and received by a device installed within the vehicle. It is compatible with standard devices and can be wired or wireless.

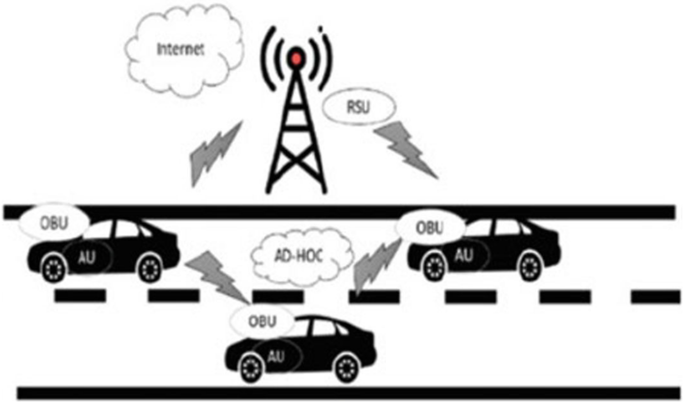


Fig. 1 Communication node [7]

- **Roadside Unit (RSU)**: It's place alongside the road, at intersections, and in parking lots. Because the internet-connected device would lead them, it will not only increase people's security but also assist them prevent mishaps.

2 Background of ML and Deep Learning

2.1 Algorithms for Machine Learning

A collection of statistical and algorithmic models known as machine learning enables computers to learn how to make data, make prediction and make decisions on that data to be applied. A few machine-learning techniques will be discussed in this section [8]:

Assistance Vector Machine Learning: A supervised method that maximizes the margin is called an SVM. This type of linear classifier performs better as complexity rises. Finding the hyperplane that divides (or nearly divides) the data into two classes is SVM's primary goal.

- **Decision Tree**: The aim to learn leaf-level decision rules and to create a model with data characteristics as input and target variable value as output.
- **Random forest**: In many application areas, RF is easy to use, quick, and efficient. An ensemble of several decision trees serves as the foundation for the training and voting stages.
- **Principal component analysis**: PCA can be used to create exploratory data analysis and prediction models. Finding the primary components and a sort of dimensionality reduction that alters the base of the data may be part of this process; it might be as easy as selecting, ignoring the rest and focusing just on the first few. In general, it is used to reduce dimensionality.

- **K-Nearest Neighbor**: A straightforward supervised learning technique for classification and regression issues is KNN. Because it doesn't require extra assumptions or multi-parameter adjustment, it is simple to understand and apply. But when dealing with big datasets, it gets drawn out. Finding the separation between a query and every piece of data, choosing the label that most closely matches your query, voting for the label that appears the most, or averaging relies on our target variables are how classification and regression problems work.
- **Reinforcement Learning**: Also known as RL, reinforcement learning is a class of machine learning issues that aims to make the best choices possible based on previous actions or occurrences.

This indicates that, in contrast to supervised and unsupervised learning, reinforcement learning is an interactive learning approach. To achieve the best result, it constantly seeks out new things (exploration), monitors the environment's results (observation), and modifies its methods (variables) [9].

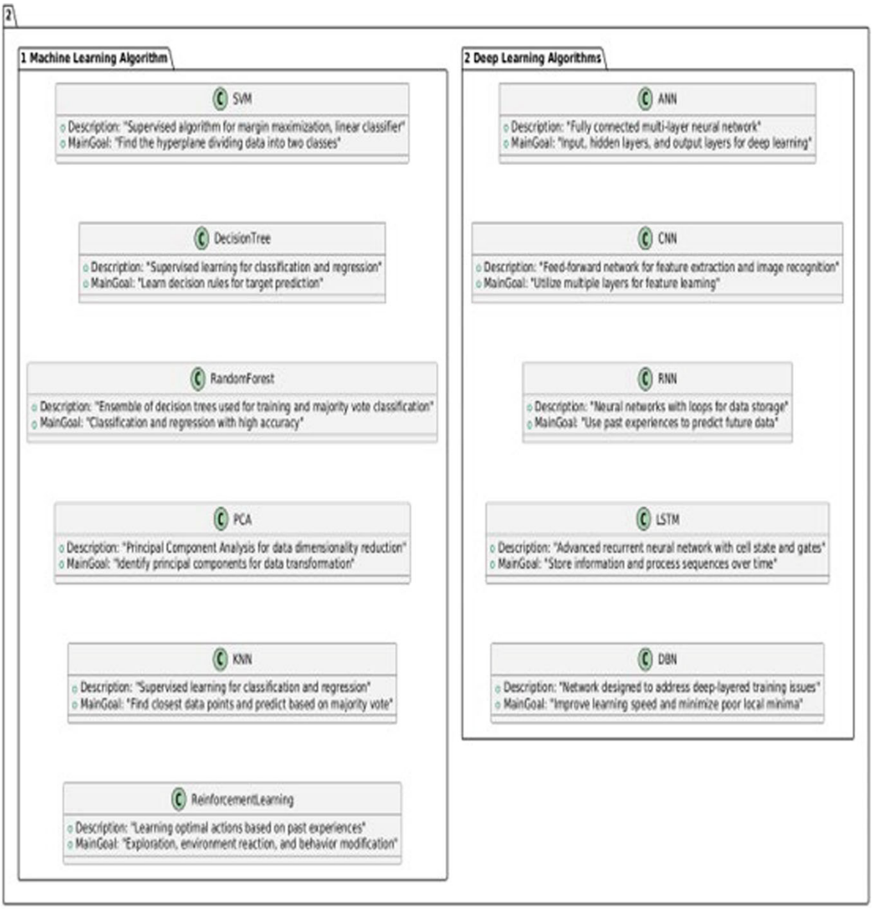
2.2 Algorithms for Deep Learning

The working of the human brain works as some inspiration for deep learning, a branch of machine learning that uses a model known as neural networks to generate predictions. A few deep-learning strategies to address this issue will be discussed in this section [10].

An input layer, several hidden layers, and an output layer make up an artificial neural network (ANN), which is a fully connected, multi-layer neural network. Every node in the top layer is linked to every other node in the bottom layer. By including more hidden layers, we expand the model's capacity.

- **CNN**: A feed-forward neural network, CNN is frequently utilized in artificial intelligence for image identification and the extraction of features. The input layer, pooling layer, full-connection layer, and output layer are the five layers that make up CNN.
- **Recurrent Neural Networks (RNNs)**: RNNs are a form of artificial neural network that can store data because of its loops. Reasoning is accomplished by recurrent neural networks to forecast the future based on these prior experiences. Because recurrent models can map vectors, this told the API that it can perform more complicated operations.
- **Long Short-Term Memory**: Modern neural networks and LSTM share an identical design. As it expands, it communicates and analyzes data. The cells in the LSTM algorithm are operating in a distinct way. The key component of the cell state and its many gates are known as LSTMs. Along the order loop, the cell state acts as a conduit for relative information.
- **Deep Belief Network**: These networks were created because traditional neural networks encountered several problems when trained on deep layered networks.

These problems include slow learning, the requirement for large training sets, and being stuck in the local minima (because of bad parameter selection) [11] (Fig. 2).



SVM
- Description: "Supervised algorithm for margin maximization, linear classifier"
- MainGoal: "Find the hyperplane dividing data into two classes"

DecisionTree
- Description: "Supervised learning for classification and regression"
- MainGoal: "Learn decision rules for target prediction"

RandomForest
- Description: "Ensemble of decision trees used for training and majority vote classification"
- MainGoal: "Classification and regression with high accuracy"

PCA
- Description: "Principal Component Analysis for data dimensionality reduction"
- MainGoal: "Identify principal components for data transformation"

KNN
- Description: "Supervised learning for classification and regression"
- MainGoal: "Find closest data points and predict based on majority vote"

ReinforcementLearning
- Description: "Learning optimal actions based on past experiences"
- MainGoal: "Exploration, environment reaction, and behavior modification"

ANN
- Description: "Fully connected multi-layer neural network"
- MainGoal: "Input, hidden layers, and output layers for deep learning"

CNN
- Description: "Feed-forward network for feature extraction and image recognition"
- MainGoal: "Utilize multiple layers for feature learning"

RNN
- Description: "Neural networks with loops for data storage"
- MainGoal: "Use past experiences to predict future data"

LSTM
- Description: "Advanced recurrent neural network with cell state and gates"
- MainGoal: "Store information and process sequences over time"

DBN
- Description: "Network designed to address deep-layered training issues"
- MainGoal: "Improve learning speed and minimize poor local minima"

Fig. 2 Overview of machine learning and deep learning algorithms: descriptions and methodologies

3 Deep Learning and Machine Learning Challenges

3.1 Security

Security is VANET's top priority. Access management, traceability, revocability, availability, reliability, transparency, repudiation, privacy, and confidentiality are some of these security features [2, 3]. Improved car drivers' perceptions of pavements close to passing cars are described in research [12].

In the presented system, by linking roadside units (RSUs) to cars, traffic is harnessed to send data concerning whether or not a pedestrian is present [1]. Such RSUs sign the alert message before distributing it, and all responding vehicles can verify that signature, thereby preventing false information from being transmitted. Such is done to comply with rigid safety protocols, for example, 6T, and avoid duplication of the alert [13]. This is to accommodate setting a minimum time for verifying messages for the presence of vehicles on the crosswalk of interest. Nimble asymmetric cryptography (NAC) is a technique that authenticates comms sent indirectly and can be taken to the signed notifications. NAC makes asymmetric coups obsolete, with the expense ratio of efficiency going up, but necessary since for the non-productive expenditure, NAC is a must. Multiple works have been done on different designs for the VANET in a sparse network; an authentication scheme based on device fingerprinting and password is proposed by Nandy et al. [14].

3.2 Privacy

Once more, the driver's identity is confidential and cannot be disclosed. The experience makes assumptions about what privacy in VANET should do with regard to certain Transitions being integrated, as demonstrated by the recognised Transitions above. The study discovers the route position learning method (DLP) and d-Adjustable k-anonymous (DAK). They are required to do PP-OSGI. The DAK and DLP algorithms choose a set of anonymous neighbours and determine the level of privacy in the surrounding area. The vehicle is the source of the incoming request to the service application, and the cars will distort the vehicle's position. Recent study, utilizing the group check in-between cars and floor units, the detection of machine control faults in full cycles must have a direct impact on safety, which is a key goal. Therefore, encrypting the messages being transferred is crucial to ensuring safe connection between the vehicle's nodes, and identifying the original nodes is only permitted with permission. Time or authentication between the vehicles is not guaranteed by the message authentication's correctness [15].

3.3 Real-Time System

The most extreme pattern of the real-time limits normal for gadget use comes especially from transport. This explains the challenge of letting other devices know when the countdown time is not up. While implementing secure data aggregation in real-time traffic vehicles, the author [14] used the principle of cloud technique at VANETs by embedding the message recovery signature in [10] contains the data recovery attribute.

3.4 Diversity and Quality of Data

VANETs produce vast amounts of heterogeneous data from sensors, cameras, and communication devices. In many cases, such data are noisy, inconsistent, and incomplete; therefore, model building with such data is daunting. Additionally, certain valuable occurrences could be rare in the datasets and can hence lead to the model's prediction bias or even be catastrophic [16].

3.5 Limitations on Resources

Such environments as VANET vehicles and roadside units (RSUs) can be resource-constrained in terms of their computational and energy resources. Specifically, if we do not use the right techniques, these devices can cause delays or entire systems to break when running resource-intensive DL models, especially in large-scale deployments [17].

4 The Use of ML and DL Algorithms in VANET

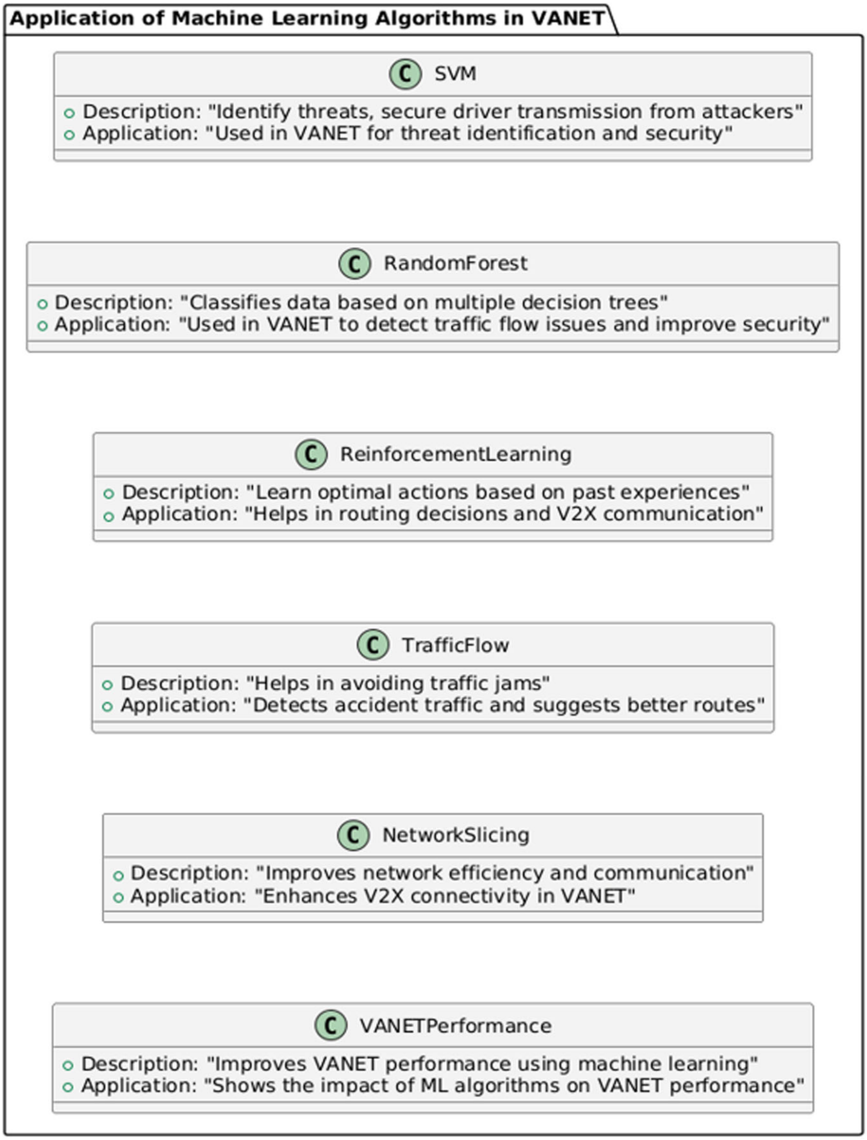
4.1 The Use of Machine Learning Algorithms

Similarly, the Vinet network is improved by using machine learning to resolve issues in this specific network. It could be hazardous and challenging for drivers, such as knowledge of hazards employing the support vector machine (SVM) and random forest (RF) methods. That helps quite a bit in ensuring the drivers' security. This will prevent traffic jams by engaging in traffic accidents and alerting the drivers to choose the right road. It is also used to handle routing decisions, network slicing, and V2X communication. This paper has enhanced some aspects of the use of machine learning in the Vinet network as provided in the following table for the area of use of each of the methods in the Vinet area with the disadvantages. Detection of gender classification using ML algorithms Machine learning is deployed and diagnosed by merging support vector machine learning (SVM) and random forest (RF) algorithms into the VANET network; this network can identify attacks and other attributes considered life-threatening or challenging for drivers. That ensures the driver's security, and that the transmission is protected from either your privacy or that of unauthorized people. Moreover, it also helps manage traffic and prevent traffic jams because it can distinguish between accidents; it might help direct drivers to choose another way if it is early enough. Besides improving V2X connection via network slicing, reinforcement learning can address routing decision problems. From Table 1, machine learning techniques with their shortcomings in the field of VANET and its applications have been explained, including their constraint. References [8, 17] have shown how eLearning can improve the quality of VANET (Fig. 3).

Table 1 The application of machine learning on Vanet and their limitations [18]

References	Machine learning algorithm	Applications	Limitations
[19]	Support Vector Machine Learning	• Making a road safety prediction • Enhanced Vanets performance • Detected DDOS attacks • Secured massive data transport using Vanets	• SVM-based models are more challenging to understand and interpret • Making them less appropriate for highway environments
[20]	Decision Trees	• Identifying malware traffic • Forecasting road safety	• Need private data • Reduced storage needs • Challenged when a lot of Dts are required
[21]	Random Forests	• Identify assaults • Identify known network breaches • Detect traffic accidents • Manage channel placement	• Required an extended duration while processing substantial data volumes • The security issue
[22]	Learning with Reinforcement	• Problems with routing decisions • Improved network slicing for V2X communications • More dynamic and equitable distribution of the spectrum for several access via different vehicles • Effective for challenging vehicle mobility	• In addition to requiring a vast amount of input and processing, • Reinforcement learning may face significant difficulties when implemented in real-world physical systems due to the large number of attributes

the VANET network's performance [19].



Application of Machine Learning Algorithms in VANET

SVM
- Description: "Identify threats, secure driver transmission from attackers"
- Application: "Used in VANET for threat identification and security"

RandomForest
- Description: "Classifies data based on multiple decision trees"
- Application: "Used in VANET to detect traffic flow issues and improve security"

ReinforcementLearning
- Description: "Learn optimal actions based on past experiences"
- Application: "Helps in routing decisions and V2X communication"

TrafficFlow
- Description: "Helps in avoiding traffic jams"
- Application: "Detects accident traffic and suggests better routes"

NetworkSlicing
- Description: "Improves network efficiency and communication"
- Application: "Enhances V2X connectivity in VANET"

VANETPerformance
- Description: "Improves VANET performance using machine learning"
- Application: "Shows the impact of ML algorithms on VANET performance"

Fig. 3 Role of machine learning algorithms in VANET

4.2 *The Use of Deep Learning Algorithms*

Deep Learning, or Neural Network, has gained most of the research, as we explained earlier, on a vast scale to incorporate its benefits and effectiveness in various fields that have been utilized to improve algorithms and methods. In the next section of this paper, let us discuss the industries in the vent where dl has been used. Some DL-based techniques could be a drawback through feature choice and data consolidation, as they choose and identify the options from information on their own [23]. CNN was found to be applied for feature extraction in many studies, and CNN is used in conjunction with other algorithms for better performance. Some of the advantages of the deep learning techniques in the virtual reality domain can be observed below points; some shortcomings of the deep learning techniques in virtual reality domain are evident from the table above listed as follows: In addition, the SP algorithm finds the optimal path in a reasonable time from source to destination rather than genetic algorithms that are ideal for solving complex optimization problems with significant constraints and network structures which also help the Vinet networks in wise decision making and act wisely in the case of accident or car crash. Selecting the most convenient shortest path between the base station and the transmitter head (cluster, node, intermediate, or advanced) is another responsibility in resolving the routing issue in an Ad Hoc network large map [24] (Table 2).

5 Innovations that Make AI a Game-Changer for VANETs

AI in VANETs has brought greater integration into how cars interact with each other and their environment, resulting in incredible advancements. These advancements make transportation systems more innovative, safer, and more efficient, thus overcoming many of the traditional limitations of the VANET systems. Key developments driving the evolution of AI-based VANETs are as follows [28].

5.1 Learning Federated

Federated training lowers network bandwidth while protecting user privacy by allowing ML models to be collaboratively trained across multiple cars without sharing raw data. This decentralized approach enables real-time model updates while ensuring adaptability to various driving scenarios [29].

5.2 AI Edge

Edge computing may facilitate the quick deployment of lightweight AI models on roadside infrastructure or in-vehicle devices. By processing data locally [30], Edge AI reduces latency, enhances real-time decision-making, and decreases dependency on centralized cloud systems.

Table 2 The application of deep learning on vanet and their limitations

References	Deep learning algorithm	Application	Limitations
[25]	ANN	• Road safety prediction • Telecommunication reliability enhancement • Throughput growth and packet dropping rate reduction • Performance enhancement • and use and deployment on cars for dos and black hole attack detection	• For better results • It should be used in conjunction with other machine learning methodologies
[18]	CNN	• Spatial and temporal feature extraction Predict traffic congestion • Accurately estimate network traffic • Handle multimedia data acquired from roadside devices or the vehicle's control camera	• Execution duration, • Input size • Inadequacy in online anomaly detection • and difficulty in deployment
[26]	RNN	• Better mobility predictions • The identification of obstacles Information sharing via cloud computing, fog, and collaborative edge	• The fundamental drawback of RNNs is the issue of gradients growing or bursting during training
[27]	LSTM	• Effective anomaly detection solution for SQL, XSS, and Dos threats • Predicts traffic congestion	• Slowest, overfitting issue, complexity when more features are introduced

5.3 Robustness to Adversarial

Adversarial robustness advancements aim to create AI models immune to malicious data inputs or disturbances. This advances safety by protecting VANETs from potential cyberattacks and ensuring dependable performance in adverse conditions [31].

5.4 Learning Transfer

DAU-trained models will then modify existing models for VANET applications through transfer learning. By reducing the computational and data demands of training, this approach accelerates the rollout of AI-based solutions over various vehicle environments [32].

5.5 GNN Graph Neural Networks

GNNs are well-suited for representing data from V2V and V2I links due to vehicular networks' inherent spatial and temporal correlations. This invention improves resource allocation, traffic prediction, and routing for VANET.

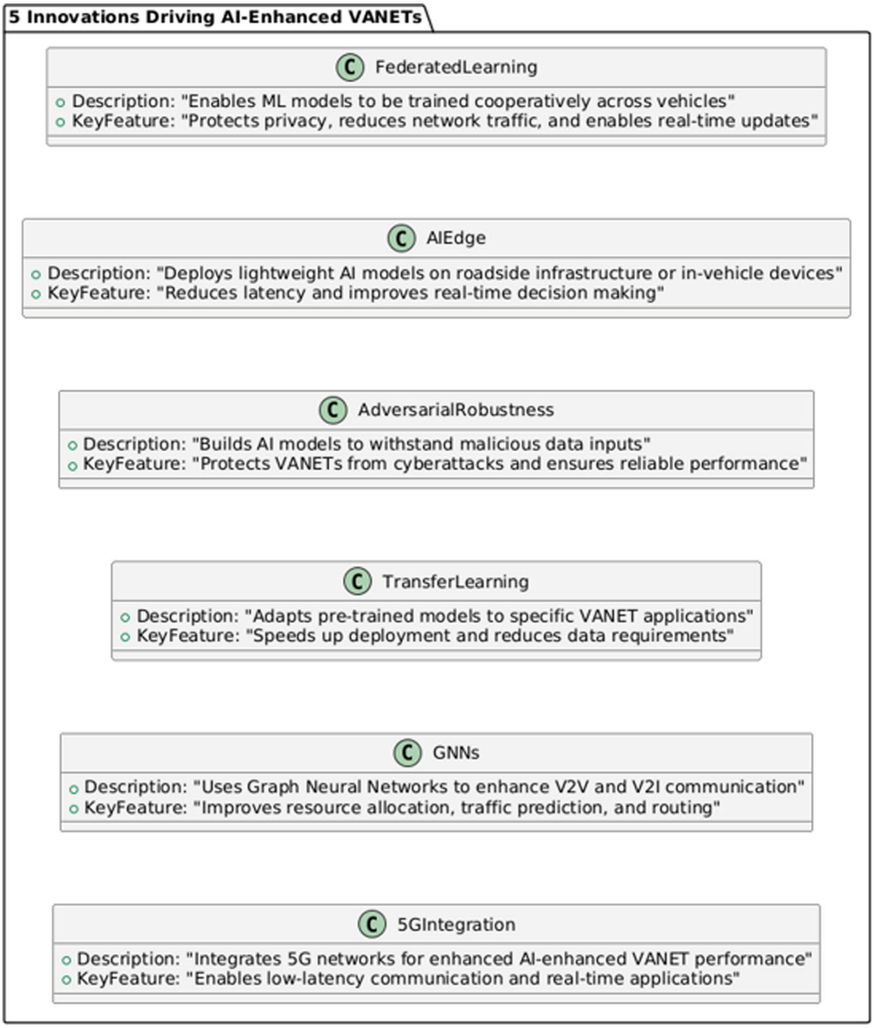
5.6 5G and Beyond Integration

5G networks' extremely dependable low latency communication (URLLC) capabilities support the performance of improved artificial intelligence (AI) based vehicular ad hoc network (VANET) [4]. The enhanced data delivery and connectivity of 5G enable seamless real-time AI applications, such as autonomous driving and collision avoidance (Fig. 4).

6 Conclusion

Vehicular Ad Hoc Networks (VANETs), which have fundamentally altered contemporary transport systems, are gradually incorporating deep learning (DL) and machine learning (ML) are examples of artificial intelligence (AI). These advancements improve traffic control, road safety, and the capacity for wise decision-making. * ML approaches such as Reinforcement Learning (RL), Support Vector Machines (SVM) and Random Forests (RF) improve routing, traffic control, and hazard identification. Similarly, DL-based methods such as long short-term memory (LSTM) networks, convolutional neural networks (CNN), and recurrent neural networks (RNN) provide sophisticated forecasting capabilities for traffic flow and road safety. The broad application of AI in VANETs is constrained by several problems, despite its potential.

Such challenges are limited computing power, real-time processing requirements, data variety, and privacy and security requirements. Federated learning, edge AI, and advances in adversarial robustness offer innovative solutions to these challenges, making VANETs scalable, secure, and responsive. To boost VANET functionality,



5 Innovations Driving AI-Enhanced VANETs

FederatedLearning
- Description: "Enables ML models to be trained cooperatively across vehicles"
- KeyFeature: "Protects privacy, reduces network traffic, and enables real-time updates"

AIEdge
- Description: "Deploys lightweight AI models on roadside infrastructure or in-vehicle devices"
- KeyFeature: "Reduces latency and improves real-time decision making"

AdversarialRobustness
- Description: "Builds AI models to withstand malicious data inputs"
- KeyFeature: "Protects VANETs from cyberattacks and ensures reliable performance"

TransferLearning
- Description: "Adapts pre-trained models to specific VANET applications"
- KeyFeature: "Speeds up deployment and reduces data requirements"

GNNs
- Description: "Uses Graph Neural Networks to enhance V2V and V2I communication"
- KeyFeature: "Improves resource allocation, traffic prediction, and routing"

5GIntegration
- Description: "Integrates 5G networks for enhanced AI-enhanced VANET performance"
- KeyFeature: "Enables low-latency communication and real-time applications"

Fig. 4 Innovations driving AI-enabled VANETs

future directions will focus on adopting advanced technologies, such as 5G, joint artificial intelligence, and green-oriented models. Digital twins and transfer learning should enable innovative, safer, and more resilient transportation networks. Stepping back barriers in denser urban contexts will create new opportunities for better environmental sustainability, mobility, and traffic safety. Ultimately, this association of the VANETs with AI sets a solid platform for future intelligent transport systems.

References

1. Sun, Z., et al.: Load-carrying capacity evaluation of girder bridge using moving vehicle. Eng. Struct. (2021)
2. Marques, F., et al.: Weigh-in-motion implementation in an old metallic railway bridge. Eng. Struct. (2016)
3. Miao, T.J., et al.: Bridge live load models from WIM data. Eng. Struct. (2002)
4. Seo, J., et al.: Bridge rating protocol using ambient trucks through structural health monitoring system. Eng. Struct. (2013)
5. Zhang, Z., et al.: Sparse signal recovery for WIM measurements from undersampled data through compressed sensing. Measurement (2020)
6. Worden, K., Cross, E.J.: On switching response surface models, with applications to the structural health monitoring of bridges. Mech. Syst. Signal Process. **98**, 139–156 (2018)
7. Jacob, B., O'Brien, E.J.: Weigh-in-motion: recent developments in Europe (2005)
8. O'Connor, A., Eichinger, E.M.: Site-specific traffic load modelling for bridge assessment. Proc. Inst. Civ. Eng. **160**(4), 185–194. Thomas Telford Ltd (2007)
9. Li, M., Huang, T.L., Liao, J.J., Zhong, J., Zhong, J.W.: WIM-based vehicle load models for urban highway bridge. Latin Am. J. Solids Struct. **17**(05), e290 (2020)
10. Kasmalkar, I.G., Serafin, K.A., Suckale, J.: Integrating urban traffic models with coastal flood maps to quantify the resilience of traffic systems to episodic coastal flooding. MethodsX **8**, 101483 (2021)
11. Chen, S.Z., Feng, D.C., Sun, Z.: Reliability-based vehicle weight limit determination for urban bridge network subjected to stochastic traffic flow considering vehicle-bridge coupling. Eng. Struct.Struct. **247**, 113166 (2021)
12. Gao, M., Gong, H., Li, X., Chen, B., Zhou, C., Shi, M., Guo, L., Chen, Z., Ni, Z., Duan, G.: Land subsidence and ground fissures in Beijing Capital International Airport (BCIA): evidence from Quasi-PS InSAR analysis. Remote Sens. **11**, 1466 (2019)
13. Lyu, M., Ke, Y., Li, X., Zhu, L., Guo, L., Gong, H.: Detection of seasonal deformation of highway overpasses using the PS-InSAR technique: a case study in Beijing urban area. Remote Sens. **12**(18), 3071 (2020)
14. Pregnolato, M., Winter, A.O., Mascarenas, D., Sen, A.D., Bates, P., Motley, M.R.: Assessing flooding impact to riverine bridges: an integrated analysis. Natural Hazards Earth Syst. Sci. Discussions **2020**, 1–18 (2020)
15. Jacob, A., Akkara, J., Jinesh, K.J., Therattil, J.P.: Effect of non-urban two lane highway geometry on car and bus drivers–a physiological study. Transp. Res. Procedia **62**, 358–365 (2022)
16. Wang, T., Liu, Y., Li, Q., Du, P., Zheng, X., Gao, Q.: State-of-the-Art review of the resilience of urban bridge networks. Sustainability **15**(2), 989 (2023)
17. Wang, X., Pang, Y., Ye, A.: Probabilistic seismic response analysis of coastal highway bridges under scour and liquefaction conditions: does the hydrodynamic effect matter? Adv. Bridge Eng. **1**, 1–15 (2020)
18. Ulvi, H., Yerlikaya, M.A., Yildiz, K.: Urban traffic mobility optimization model: a novel mathematical approach for predictive urban traffic analysis. Appl. Sci. **14**(13) (2024). https://doi.org/10.3390/app14135873
19. Hełdak, M., Kurt Konakoglu, S.S., Kurdoglu, B.C., Goksal, H., Przybyła, B., Kazak, J.K.: The role and importance of a footbridge suspended over a highway in the opinion of its users—Trabzon (Turkey). Land **10**(4), 340 (2021)
20. Mahamid, M., Ozevin, D., Torra-Bilal, I., Kabir, M., Mastny, S., Khudeira, S., Sauter, B.W., Zroka, D.: Structural design and inspectability of highway bridges. Pract. Period. Struct. Des. Constr.. Period. Struct. Des. Constr. **24**(3), 06019002 (2019)
21. Banerjee, S., Vishwanath, B.S., Devendiran, D.K.: Multihazard resilience of highway bridges and bridge networks: a review. Struct. Infrastruct. Eng.. Infrastruct. Eng. **15**(12), 1694–1714 (2019)

22. Han, Z.: Aesthetics innovation and practice of urban bridge design. Struct. Eng. Int.. Eng. Int. **31**(4), 543–549 (2021). https://doi.org/10.1080/10168664.2020.1848368
23. V. Farhangi and M. Karakouzian, 'Design of Bridge Foundations Using Reinforced Micropiles'.
24. An, Y., Chatzi, E., Sim, S.H., Laflamme, S., Blachowski, B., Ou, J.: Recent progress and future trends on damage identification methods for bridge structures. John Wiley and Sons Ltd (2019). https://doi.org/10.1002/stc.2416
25. Zhou, M., Lu, W., Song, J., Lee, G.C.: Application of ultra-high performance concrete in bridge engineering. Elsevier Ltd (2018). https://doi.org/10.1016/j.conbuildmat.2018.08.036
26. Zambrano-Martinez, J.L., Calafate, C.T., Soler, D., Cano, J.C., Manzoni, P.: Modeling and characterization of traffic flows in urban environments. Sensors **18**(7) (2018). https://doi.org/10.3390/s18072020
27. Gao, Y., Zhu, J.: Characteristics, impacts and trends of urban transportation. Encyclopedia **2**(2), 1168–1182 (2022). https://doi.org/10.3390/encyclopedia2020078
28. Allam, Z., Sharifi, A.: Research structure and trends of smart urban mobility. Smart Cities **5**(2), 539–561 (2022). https://doi.org/10.3390/smartcities5020029
29. Abdal, S., et al.: Application of ultra-high-performance concrete in bridge engineering: current status, limitations, challenges, and future prospects. MDPI (2023). https://doi.org/10.3390/buildings13010185
30. Tang, D., Huang, M.: The sustainable development of bridges in China: collapse cause analysis, existing management dilemmas and potential solutions. Multidisciplinary Digital Publishing Institute (MDPI) (2024). https://doi.org/10.3390/buildings14020419
31. Oladimeji, D., Gupta, K., Kose, N.A., Gundogan, K., Ge, L., Liang, F.: Smart transportation: an overview of technologies and applications. MDPI (2023). https://doi.org/10.3390/s23083880
32. Guo, H., Huang, R., Xu, Z.: The design of intelligent highway transportation system in smart city based on the internet of things. Sci. Rep. **14**(1) (2024). https://doi.org/10.1038/s41598-024-79903-0

Intelligent Route Navigation in VANETs Using Deep Learning

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Abstract Vehicular Ad-hoc Networks (VANETs) has changed the transportation environment in a big way through car-to-car (V2V) and car-to-road Vehicle-to-Infrastructure (V2I) communications. In VANETs, good route planning plays an indispensable role in achieving a safer, more efficient transportation system. This project proposes a novel deep learning-based approach for next-generation route planning algorithms in VANETs. Using the power of deep learning, our method tries to achieve optimal route planning in VANETs, decreasing travel time, and emissions whilst increasing total throughput of transportation. Our proposed algorithm combines on-road traffic information and the road conditions in the outdoor environment with some environmental factors to forecast optimized routes in the dynamic VANET environments. The presented method is tested in an extensive simulation environment, which illustrates the potential of the proposed method to substantially enhance the effectiveness and the safety of route planning in VANETs. These studies have important potential applications for the advancement of intelligent transportation systems, smarter and greener urban mobility.

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1 Introduction

Vehicular Ad hoc Networks in which vehicles work like nodes to create Mobile Ad hoc Networks are one of the broad classes of mobile ad hoc networks. Vehicular Ad hoc Networks provides vehicle-to-vehicle connection (V2V) because it stores and retrieves data in cars. Conversely, Vehicle-to-Infrastructure (V2I) communication involves sending messages from roadside vehicle communications such as traffic lights, toll barriers, or police stations, towards the vehicles. VANETs provide a safer environment on roads and improve transport throughput with reduced pollution. Therefore, the development of useful routes in VANETs is very important because of its convenience [1].

Proper pathway planning is the most critical aspect considered for complete communication in VANET. However, the task is challenging because of constraints, such as limited bandwidth, network connectivity, high-speed mobility of blood, and topologies that can vary across time. In line with these limitations, the bring-about requirement of the state-of-the-art routing solutions in VANETs is to manage the congestion in these route plans. Routing protocols or paths should minimize or avoid control overhead and be able to achieve these benefits in VANET. More so, appropriately utilized bandwidth and mechanisms that use the service quality of treatment as well as robustness to network attack would be there.

Topology-based protocols are those that consider information like speed and direction, link status, and the distance between vehicles for route constructions. Position-based protocols use GPS coordinates to determine the exact position of vehicles on the map. Beacon-based protocols send out such signaling waves after a regular interval to establish route and maintain it. Finally, mixed-type protocols can have reactive or proactive discoveries and multiple classes of packets can be used to find the path. Recent possible contributions are leveraging deep learning and machine learning.

2 Overview of VANETs

Despite Flow-Service-Quality (FSQ), there have been Vehicular Ad-hoc Networks (VANETs) deployed in recent years. Admittedly, the passive nature of vehicular communication has taken a new dimension through this evolution, forging a super connected form of communication among vehicles or between vehicles and roadside infrastructure. Being dedicated to such knowledge, it is assumed to lead to improving road safety and efficiency by letting the vehicles, the infrastructure, and the internet share this data securely. The system requires DSLC or other established specifications so that vehicles can send safety messages up to 1000 feet away at speeds that allow these devices not to accept unwarranted interference. The vehicles should be designed with enough equipment to allow transmission and reception of such messages to create an ad hoc wireless network among themselves while on the road. True to the power of the Internet and infrastructure, cars can convey or receive messages of safety or traffic through cellular networks (3G-5G), IEEE 802.11p/WAVE protocol, or other unattended long-range networks such as LoRa involving vehicles and network nodes [2].

VANETs offer various salient applications for safe travel, traffic management, and infotainment. Warnings include changing lanes, the risk of collision ahead, crossroad support, and impaired visibility. Traffic management applications are best suited for traffic light control were traffic light control operation by monitoring as well as actively managing vehicular speeds in and around the traffic jam.

Infotainment services provide real-time information regarding amenities, weather, news, and all information affecting traffic. The messages exchanged between vehicles extend to proactive safety messages-which include the speed, direction, and position of the vehicle and additional parameters-as well as usual messages about road events such as accidents and vehicle breakdowns. A standard pattern has been adopted where proactive safety messages depict the data as part of their contribution, every unknown time and every specific message regarding an incident occurring (Fig. 1).

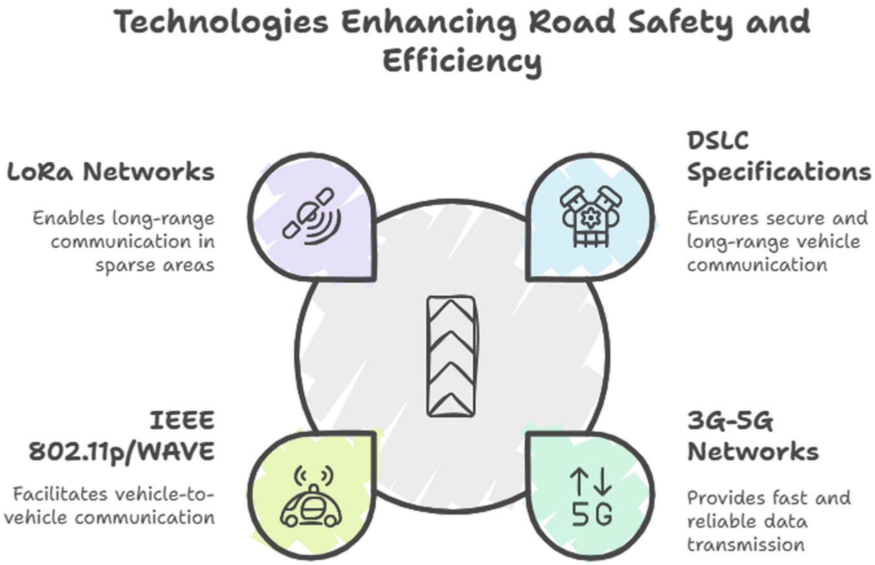
Technologies Enhancing Road Safety and Efficiency
LoRa Networks
Enables long-range communication in sparse areas
DSLC Specifications
Ensures secure and long-range vehicle communication
IEEE 802.11p/WAVE
Facilitates vehicle-to-vehicle communication
3G-5G Networks
Provides fast and reliable data transmission
5G

Fig. 1 Categorization of routing protocols using VANETs

3 Importance of Route Planning Algorithms

It is the process where a network can identify the most efficient way to go and supply a visitor, for example, from some first place to some eventual destination. Mostly, route planning with respect to a map of the road network ought to define a countable collection of waypoints or set of points made up of the journey itself. Route planning includes evaluation of all possible tradeoffs between the most efficient, shortest, best on fuel, or easiest on the environment way to construct each path such that the fast response that would usually be needed—action in milliseconds—can become a completely state-vector form mapping all waypoints in a system of matrices that would map best to that matrix.

Before the journey even starts, the possible ways a person might follow to reach a destination can be determined. On-the-fly route planning could also be employed while traveling along it is using the road network. Some roads might also have to be updated due to changes in the network like accidents or roadblocks. Traditionally, deterministic algorithms have been employed for route planning activities. With recent developments in deep learning, the use of neural network function approximators has ushered in a new breed of algorithms that promise very quick generalization across learning domains. These are impressive when it comes to fast route planning compared to deterministic algorithms, which, in stark contrast, usually calculate said routes by exhaustively searching through tissues with differing degrees of pitch and shape rather than using approximations to establish models [2].

Recently, new deep learning approaches in the context of path planning have been proposed considering static networks, road networks for on-demand vehicles, and autonomous vehicles in urban areas. Network designs may be static or dynamic. A static network is one that does not change over time, whereas a dynamic network undergoes modification to it through the inclusion or removal of nodes or edges. Route planning, by definition, would take place at the static network where the aim is to find a route that accommodates specified constraints in the network being diverted to a pre-determined objective in order to optimize. This problem of route planning is evidently problematic with static network where no edge or node is added or removed over time, and the pattern in traveling time along itself was constant. Solution approaches may include combinatorial search, such as: routes are obtained by scratch searching across network candidate solutions, or by raiding a search space on the basis of heuristics, as well as network simplex methods [3].

4 Traditional Route Planning

Algorithms in VANETs Through the advancements in wireless communication technologies, vehicles started acting as mobile sensing platforms of not only collecting and sending data on the status of the road, neighboring infrastructures, and data traffic but offer rich information to this effect. In the development of smart transportation systems, vehicular networks are an important ground for vehicles to connect with roadside units or other vehicles. Roadside units connect vehicles to maintain driving convenience and safety access. Such convenience in driving requires the exchange of a substantially huge amount of data [4]. They are fixed infrastructural applications deployed along the road; provide services that can be delivered to vehicles. A Road-Side Units (RSU) comes with a wireless communication device to connect with other vehicles for real-time and reduced delays in data transmissions and high data rates. RSUs have internet connectivity to allow the uploading of collected vehicle data to cloud servers for processing. RSUs could be installed with traffic cameras and vehicle identification systems to monitor different aspects of the vehicles' speed and identify any vehicle infringements, and the captured data could be forwarded to a police department for further action. Vehicles also have the privilege to access collected data by RSUs, such as information on the state of the road network, which is important for route planning. Route planning gives specific waypoints in the road map that the vehicle must follow and permits the selection of one of the many evaluation measures, often the shortest path. This is the single most important thing to accomplish in autonomous vehicle technology: how to plan a trajectory without human intervention. Traditionally, deterministic algorithms are used for huge path planning, those algorithms being dependent on a static map or world graph for road networks. To give a very brief description, a deterministic planning process actually assumes the existence of complete and static information for processing by its decision-making procedure Plan for route planning, on the other hand, identifiable in exploration, involves the mobile agent and technology to contain information about the surrounding environment, thus accomplishing the synthesis required for planning (Fig. 2).

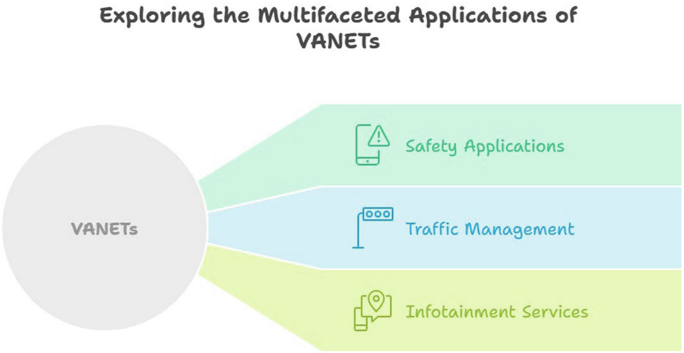

Fig. 2 Categorization of applications of VANETs

4.1 Motivation for Deep Learning Approach

A routing protocol, known as a Deep Learning routing protocol-Black Hole Avoidance Protocol based on Deep Learning in VANETs [5], wherein DL technique is modeled for the generation of selected and most efficient routes working against black hole attacks. The routes will be established as far as travel through two procedures, and these are route discovery and route maintenance. This will surely discover a black hole which previously contacted a faked route request sent to all its neighboring nodes. Node answer will then undergo comparison with the fitness function value, and a basic Dijkstra Node is usually considered to have more fitness function value over and above a black hole node. Using DL, the fitness function value of the node will be determined; thereby, a black hole node may not be selected itself. The descending route may also be constructed through the lowest fitness function value. This effect will ensure a dramatic speedup in optimization and provide rapid construction of new routes when delays greater than threshold dramatically lower delays during the optimization process and in sustaining the entire route. Training the DL permits the model to spot the relationship between input and output information, removing the requirement for additional procedures, thus when employing this model with a network, it could define whether the next node is a black hole attack node based on its fitness function value as well as the speed of its optimization in relation to the basic Dijkstra line by contrasting the number of packages lost. However, the increase in network size will increase packets lost on Dijkstra, hence a DL model may prevent pathogens from creating or slowing down delays significantly and, as a consequence, improve the overall performance of the system. Reinforcement learning setup for advanced vehicular ad hoc network communication system Vehicular ad hocs (VANETs) have become very favorable and advantageous for automotive industry. The networks will enhance comfort and safety for drivers and pedestrians being used by drivers and pedestrians. Communication is possible from vehicle to vehicle as well as between vehicles and fixed services. Furthermore, the vehicles will communicate with the internet in order to provide many additional services to their passengers. There are new technologies that are being implemented. Typical VANETs can be transformed into advanced VANETs by incorporating them. Their addition will enhance the communication efficiency and safety of the transportation infrastructure. Because there are more technical prospects opening, the new obstacles must be solved by improved techniques and architecture. Routing a message across the network is one such basic activity. In networks such as these ad-hoc networks, every node determines independently where to send the message that it wants to send. This network does not have taken fixed parameters into account and it is also made up of several mobile nodes that make routing in varying environment, and hence in a mobile ad-hoc network, very complicated. The nodes seem to move continuously, and it is hard to predict anything about their movements. Thus, using this method, it will be difficult to find the best route through which to reach an end destination, because it is difficult to predict the links that will fail during the communication event. Many studies have proposed remedies for knowledge-based and topology-aware proactive routing and hold promises for a new initiative which may eventually make a significant improvement in routing in MANETs [6].

4.2 Fundamentals of VANETs

Vehicular networks are a subset of mobile ad hoc networks or MANETs in which vehicles serve as both data sources and mobile nodes. In VANETs, the equipped vehicles communicate among themselves and with roadside infrastructure also fitted with wireless communications. Video data is generally large, but multicasting is more effective in terms of data distribution than that of unicast, and thus, wireless stationary points can provide a network service to these points. Like the vehicle, which can act as a service provider, the use of roadside infrastructure to act as a service requester is applicable. In many VANETs, speeds of up to 120 km/h (about 33 m/s) could have been realized depending on different parameters. Moreover, since these vehicles could cycle long distances within a short period of time, the topology was changing fast, and links had to be established and destroyed between vehicle nodes at an average rate as much as 94 times over 60 s [6].

4.3 Basic Concepts and Architecture of VANETs

Ad hoc vehicular network, or VANET, is a type of mobile ad hoc network or VANET that consists of vehicle-side wireless communications devices. These lines of cars are faster than typical wireless network users. The ground transport mode is transforming into smarter vehicles or rather. The manifestations are becoming associated with connected vehicle era. Examples include a new generation of vehicles equipped with advanced in-vehicle information and entertainment communication systems. These systems are known collectively in-vehicle networks. They usually feature in-vehicle subnetworks and external vehicle-to-vehicle networks, which are sometimes referred to as VANETs. Transport networks often share the characteristic that a node's connectivity varies widely over time because of the high mobility of vehicles. At the same time, the character is significant for reducing insecurity and inconvenience.

ICT is crucial to intelligent transport systems (ITS), which ensures the safe, efficient, and environmentally sustainable movement of people and used goods. Relevant real-time information exchange among vehicles and infrastructure enables the vehicle to follow its desired trajectory, leading to an optimal traffic flow. Vehicular Ad-Hoc Networks represent a specific subclass of mobile ad-hoc networks and are created when vehicles are equipped with wireless communication devices. They speak with each other (V2V for vehicle-to-vehicle communication), as well as with roadside units (V2I for vehicle-to infrastructure communication). Roadside units, basically static stations located along the road, can be used to connect the VANET created from the vehicles with the larger internet. VANETs are further categorized as safety-critical applications or non-safety critical applications. Where safety-critical applications entail continuous exchange of information from vehicle to vehicle to secure safe driving environments, non-safety critical applications improve driving comfort and efficiency through information [7].

5 Challenges and Limitations of VANETs

They are a type of Intelligent Transportation System (ITS) technology and allow vehicles to communicate through short distance wireless networking linking vehicles and road infrastructure. It is built over the technology of WAVE (a combination of IEEE 802.11p with the upper layer protocol stack that enables the information exchange both safety-related and non-safety-related). VANETs are observed for communication area that can be divided into three subnets, namely, vehicle-to-vehicle (V2V) subnet, vehicle to infrastructure (V2I) subnet, and roadside to vehicle (R2V) subnet. Each of the subnets has its own topology within the network [8].

Safety awareness can only be realized if vehicles keep on sending safety messages such as emergency braking, collision warning, and lane change. The author argues that safety messages with highly prioritized functionalities should be relayed, or at least at the expense of other lower priority non-safety messages. Besides, it still needs to consider the spatio-temporal validity in each message. However, for example, there is a situation in which none of these non-safety messages (e.g., traffic information, advertisement) should get to the final recipient when it expires. That is why safety and non-safety route planning algorithms will be optimized separately (Fig. 3).

5.1 Deep Learning Basics

Vehicular ad hoc networks (VANETs) are the subcategory of mobile ad hoc networks (MANETs) which pervade the fields of artificial intelligence (AI) and this is taken from them. They are extensively used in the context of vehicles and road-related infrastructure by the medium of a wireless connection. In using algorithms underpinned by AI, fleet management and safeguard against mishaps could be something game-changing in VANET applications. However, it does take the complication a notch higher when applied to predictive analytics. Smart vehicles flood edge/fog devices with data to such an extent that real instantiation of low latency in machine learning analytics becomes impossible for them to perform. This part offers the general introduction of deep learning algorithms [9] and various thoughts concerning their usage in route mapping.

For the task of a mutual multi-task VANET scenario, a hybrid configuration of edge and fog computing, i.e., DNA approach, has been always presented to train/upgrade model-sagacious deep learning models. ODA will drag off raw vehicular data from the various network edge devices to fog for preprocesses and training

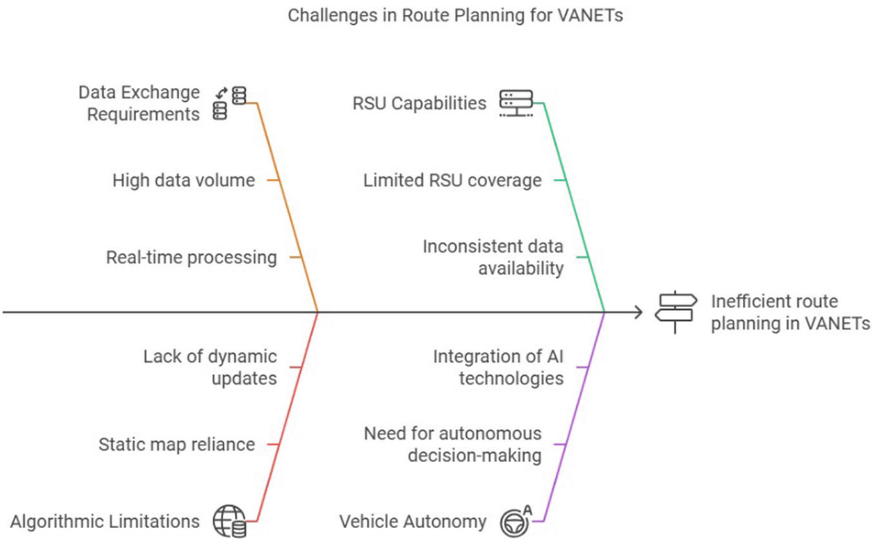
Challenges in Route Planning for VANETs
Data Exchange Requirements
High data volume
Real-time processing
RSU Capabilities
Limited RSU coverage
Inconsistent data availability
Inefficient route planning in VANETs
Lack of dynamic updates
Static map reliance
Algorithmic Limitations
Integration of AI technologies
Need for autonomous decision-making
Vehicle Autonomy

Fig. 3 Challenges in VANETs route planning

deep learning models using a data analytics node (DAN) within fog. The developed models are deployed in the edge nodes for lifelong learning supported by clustering homologous data on the edge, locating the nearest DAN, and offloading the further reservation data. The ultimate value of the efficacy of the model is tested through numerous simulations in terms of accuracy, bandwidth, and compositional distance.

5.2 *Introduction to Deep Learning*

Deep learning (DL) is a subset beneath machine learning that possesses up to three layers of neural networks. DL ventures mimic biological systems: an information processor such as the human brain. DNN, CNN, and RNN are some examples of techniques evolved in DL. The stochastically trained DNN uses disconnection to show ideal improvement in accuracy. Neural networks are set of interconnected nodes arranged in layers, for ex-input, hidden, output. And each of these connections have associated weights, which during training, get tuned to enhance the message between the nodes. When the signal exceeds a certain threshold, that should activate the node, after which the output is sent through other nodes in the subsequent layer.

It is about presenting data and targets, interfering with data through a network, coming out with predictions, and matching it against targets using a loss function. Network reruns different adjustments of the weights from time to time, using the backpropagation and optimization techniques for quality loss minimization. Deep

Learning, thus, dominates vehicular ad hoc networks (VANETs) owing to characteristics such as misleading patterns of traffic flow detection and selection by certain attackers to follow up the virulent avenues. The Deep Learning (DL) model offers better computational accuracy, data noise robustness and resistance compared with traditional methods. Routing protocols integrated with traffic classification algorithms make hugely efficient resource-saver and safety and comfort give-away to vehicles [9].

5.3 Deep Learning Architectures and Models

Over recent years, the most widely applied technique of global vehicle ad hoc networks (VANETs) is the application of Artificial Intelligence (AI) to address applications, control, and security purposes. The emergence of deep learning (DL), a subset of artificial intelligence using a stack of feedforward neural networks, can provide an enterprise- or industry-specific solution that has even higher representation capabilities and flexibility in sorting through information [9]. These DL capabilities are perceived as suitable for several applications in VANETs, such as traffic sign detection and recognition, vehicle classification, route planning, crossroad management, and collision avoidance, among others. Concerning all other applications for VANET, route planning remains vital. Vehicles must find the most suitable paths to reach their destinations as quickly and effectively as possible in this type of network. In general, cars exchange information that makes topological multiplicity available to different paths, and, therefore, vehicles decide for the one able to circumvent various constraints among them. There are different ways to justify empirical route planning in VANET-based, such as Dijkstra's algorithm, A*, Ant Colony Optimization (ACO). However, the number of AI techniques become prominent, so that several route planning algorithms are introduced using machine learning in VANETs through Decision Tree and Deep Q-Network (DQN) approaches; also based on Neural Network-based and Reinforcement Learning (RL)-based. This article involves how to make the most appropriate routes through deep learning (DL) architecture and models in VANETs. A deep learning-based vehicle routing algorithm has been proposed for using a feedforward deep neural network (DNN) model to determine feasible routes among multiple routes depending on the input about the vehicle and routes. The DNN model is trained offline using vehicle speed and distance setup, as well as the location of the vehicle in global coordinates. The trained DNN model is then employed in the online route planning platform to optimize the route. A comparison of system performance will be followed through the proposed method with those following conventional approaches, the Dijkstra algorithm, DQN, and a Deep Neural Network (DNN) regression model, for the improvement on the time and length of delay in travel of the vehicle during route planning.

5.4 Training and Evaluation of Deep Learning Models

Loop Routing Agent was implemented to study Keras python library implemented in Python programming language to learn and implement the intelligence needed for adaptive routing in Loop Vanet scenario. An agent is a network of MLP policy Deep Learning, Virtualization Environment (which simulates Loop Vanet scenario), and a static set of training, evaluation vehicles with 130 routes. Exchange happens between files in src folder.

It runs through 130 vehicles in the Loop Vanets using Reinforcement Learning API to hold 2-h simulations each in demonstration. For learning, they used the routing solutions built with the policy network trained in 3000 iterations simulated through 10-min epochs. The network is saved per 100 iterations, with the last six models used for evaluation. With the definition of the simulation environment rewards function and the vehicle settings, the input static vehicle files define vehicles by type, position and ways of routing, whereas the transfer files take care of the network model and iteration settings.

Encourage message delivery rewards are 1st and 2nd to arrive at a target through forwarding routes shorter than those required by direct communication. Reward 3 contribution is that it only calls for access to view info-entertainment messages if it is in-range towards the destination vehicle; A Loop VANET scenario is created by the package with 250 road vehicles. It consists of 3 roads connected in circular form, with a length of 500 m for the road net and 250 vehicles, including vehicles with fixed route plan to be located in the 0.5-to 3-s-interval arrival at 130 routes. Fixed arrival vehicles increase throughput and tests scenario for up to 300 s. Each vehicle on loop route plans 12 hops in 300 s simulation with max hop of 10. Each vehicle transfers one data pack every 30 s with random drawing of source and destination vehicle IDs. Packets include unique ID, source and destination, type of message, and time stamp [8].

5.5 Applications for Deep Learning in VANETs

Mobile Ad Hoc Networks (MANET) are the most useful mechanism that supports communications among vehicles and between vehicles and RSUs equipped with network devices Vehicle Ad-Hoc Networks (VANET). Such networks indeed play a critical role in the development of Intelligent Transportation Systems (ITS) with an aim to enhance road safety and traffic efficiency. Until a few years ago, considerable advancement was made in Deep Learning (DL) techniques. DL systems with multiple hidden layers, colloquially nicknamed Artificial Neural Networks (ANN), have proven to bring about substantial improvement in countless application areas, including the likes of computer vision, data mining, pattern recognition, and time-series prediction. The VANET society has started to take DL into use for everything from data dissemination, security, clustering, data aggregation, routing, to channel access. The exploration in the text shifts to a systematic review of DL studies in the context of VANETs with a primary focus on both highway and urban areas. The goals of the research involve capturing the representations of input and output data in the chosen DL architecture, covering the types of DL models used, and providing some performance metrics. Additionally, it highlights the research gaps and future research directions. This part is divided into several sections, starting with the introduction of VANETs and DL. The methodology by which relevant studies were selected is detailed, followed by a review of DL applications in VANETs in various environments and a trend of research analysis. It is also the last part of the research to discuss research gaps and future directions [10]. This paper provides a comprehensive review of various methods such as reinforcement learning, deep reinforcement learning, and fuzzy learning in the traffic network, to obtain the best method for finding optimal routing in the VANET network [11].

5.6 Traffic Prediction

Wireless connectivity for short-range communications is paramount from the view of developing and moving toward advanced assistance and safety services via a Mobile Ad-hoc Network in Vehicles (VANETs). Safety services must be quick and, therefore, require random access protocols because applications need to have the shortest possible reaction time for emergency, disaster, or distress. In case of inappropriate use, especially considering the heavy traffic conditions incurred in an urban set-up, a safety message may not reach a vehicle at the critical time that it requires. It is necessary to study traffic prediction to derive and even to enhance dissemination protocols for messages that are in fact much more efficient [12].

Traffic prediction is necessary for a VANET since vehicles' current and future positions along the same road segment aid in communicating valuable information about the traffic conditions. By employing those technologies of predictive locations, a roadside unit can give over the power to control vehicles from point of view control of users. For instance, route prediction is important from the services' point of view to a particular car. Such as a vehicle that is trying to get access to the Internet will be sent to an access point in thinking about its route. Also, route prediction may play an important role in warning the vehicle of the possible place of a dangerous traffic event [12].

5.7 Resource Allocation

Efficient and low end to end delay are required for applications like advanced vehicular safety, enhancement of traffic efficiency, and infotainment services in vehicular networks. Such applications can be catered to by V2X communication between the Vehicle-to-Everything. So far many have studied and made it possible for DSRC to be the first standard for V2X communications. Results reported in the study of GS01. Mobile communications with literally unlimited total flexibility in the context of limited spectral efficiency and bandwidth cannot meet technology's forced modernity characterization-a total impossibility for meeting the needs of advanced vehicular applications.

5G New Radio (NR) holds a lot of promise when it comes to supporting most of the above-mentioned advanced vehicular applications in V2X Communication. Another technology that offers a considerable promise for V2X Communications is 5G Technology; it is also one of the enhanced versions, with ideal characteristics of 5G technology and New Radio in the direction of massive automotive applications. The performance of V2X networks critically depends on the efficient use of available resources. Transmission resource allocation is a critical aspect that helps in maximizing network performance through the optimally shared resources.

Many techniques are proposed for performing the optimal allocation of resources in V2X communications, which in practice is a difficult problem. Resource allocation problem in V2X networks is all the more challenging due to the resource contention from different network nodes such as vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and fluctuations in space–time varying channel conditions from high mobility. The allocation of resources in V2X communications has been highly researched considering approaches like game theory, optimization theory, learning-based approaches and deep learning [8]. The emergence of deep learning-based approaches brought responses to learning-based and model-based method advantages and emerged as the most sought-after method to provide solutions for resource allocation in V2X networks [13].

5.8 Anomaly Detection

While the detection of anomalies is of paramount importance for vehicles in ensuring their safety as well as providing users with better overall vehicle usage experience, cases involving traffic accidents, roadway blockages, and sudden breakdown of vehicles creates a dangerous environment for drivers. Someone needs to be informed of anomalies at work in traffic. These abilities should be given to vehicles from incidents that appear in traffic. Thus, we prefer to consider this as an incident detection in traffic. The incident detection framework for vehicles is now possible for the proposal. Everything depends on the incidents by which vehicles are put through. Vehicles exchange information over the road through dedicated short-range in all respects to the state of the vehicle. A machine learning model is implemented in each of the vehicles for the purpose of distributed incident detection (The proposed requires feed-forward neural networks and long short-term memory model paradigms to detect road traffic anomalies gathered from the history of vehicles by auspices from vehicular ad hoc network). The models are trained and evaluated on traffic datasets. It gave 95.3% accuracy with one dataset and 85.4% with the other. A Connected Vehicle (CV) system helps to bring up enhanced operational safety, efficiency, and mobility in the road transport system by helping vehicles get their environment's information, i.e. their surroundings. To this end, vehicles have a CV system that enables better communication between vehicles, as well as with roadside units. It also enables the display of environmental data like road and traffic conditions, position of the vehicles, and speed of the vehicles, besides it can get a potential attack from different attacks that could be performed due to several securities. One such threat for secure communication at the CV system is the basic form of a malicious vehicle that could deceive other vehicles by providing them with incorrect or tampered information. To empower these vehicles to validate against information received from other vehicles, such an anomaly-based cross-layer approach of message authentication is proposed to be implemented for verification of the information exchanged amongst the vehicles in the CV system. Vehicles run a Deep Autoencoder model to detect the anomalies in the vehicle location information. The model is trained with benign data to learn a representation of the input data and to be able to detect anomalies based on reconstruction errors of the input data. Ancillary ways of detecting anomalies are using the original vehicle location data as inputs with the model predicting if the data are anomalous or not based on the predefined threshold of the reconstruction error [4, 5].

5.9 Next-Gen Route Planning Algorithms

The novel deep learning-based architecture of the future focuses on introducing next generation route planning (RNP) algorithms for vehicular ad hoc networking and connected vehicles. In-depth detailing has been carried out concerning the translation of the RNP solutions into good deep learning models, with extensive simulation analysis. Results underscore neural networks (NNs) as fairly good approximators of RNP solutions, which are further shown to achieve VT communication costs and latency equivalent to those in classical solutions, thus bringing down the model complexity quite down. This work mainly identifies the direction for future research in the area, enhancing the deep learning architecture for more complex mobility management solutions in VANETs. He noted the growing interest in communication systems, designing learning mechanisms that emulate the brain's ability to "learn" from previous experiences. These new networks will aim at maximizing the performance metrics, including delay and loss ratios, through parameter adjustment based on continuous monitoring of service quality. This emerged with respect to deep learning where a hierarchy of information processing levels, realized by neural networks (NNs), is trained with plenty of data to perform specific tasks. The lowest layers in the network learn generic properties of the input data whereas the topmost neural network consists of outputs adapted to the specific application. Once trained, the network is intended to be a "snapshot" of the acquired knowledge [14].

The Deep Learning technology growth in the field of artificial intelligence features more benefits when applied in vast applications. It goes over the existing routing algorithms for VANETs through deep learning classification, which finally determines the best routing algorithm out of the four existing traditional routing algorithms of network type, spacing, and pause time for that situation. From the traditional routing algorithm, many experiments have been done under such parameters as network size, speed, and pause time. Such traditional routing algorithms result is then input into the DL model as features for DL; these models then trained and evaluated in terms of most parameters within layers in their architectures [4]. More Parameters are checked for 100 epocs of training with various numbers of hidden layer and hidden layer neurons so that the results analyses could be based upon this numbered value. The model with two hidden layers and 50 hidden layer neurons, can achieve the highest level of accuracy: 99.5%. Finally, the 70 distinct situations are used to test the final DL model classification on the most ideal routing algorithm, with an overall accuracy of 97.14%.

VANET (Vehicular Ad-hoc Network): a network where the vehicles have on-board units that allow communication with roadside units as well as between the vehicles themselves. RSUs are immobile and can be connected to the public internet, through which a vehicle can enter communication to the world outside the VANET. The safety information of one vehicle can be passed to another for both to warn each other there is an unsafe scenario or poor roads. Through exchanging traffic information, traffic flow management improves into a very timely speed and positioning exchange between Vehicle-to-vehicle and Infrastructure-to-Vehicle. Not now, but in future traffic will be supplemented by the above with multimedia applications like video streaming and audio exchanges. Mobile station speed, the quickly changing buildings, access point light, and certain safety requirements make operation of a vanets routing protocol very challenging [2, 8].

6 Convolutional Neural Networks for Route Planning

Highly advanced sensors, wireless communication features, and on-board computability in cars have helped in promoting the advent of VANETs. Associated cars will produce a future grounded in safe road transport systems, increased traffic performance and minimal vehicles' impact on the environment. Among the uses of connected cars are vehicle planning applications, an essential instrument of future action plans of the cars that generates waypoints sequence that typically has a road map of the environment with other additional information concerning static as well as dynamic characteristics. Route planning confines the way a vehicle is artificially generated from one or more steps in time. Each of these is planned when input is provided through this planning system and its road map, including additional data describing static and dynamic features. It becomes necessary to predict the path that meets the desired operational objectives through the road network for route planning, without which application cannot work properly in connected and automated vehicles (CAVs). With the rapid growth of the Internet of Things and coupled applications in transportation, vehicles turn into CAVs that can sense the surrounding environment, taking decisions, and actions. Route planning in VANETs is a complex real-time decision problem where one needs to generate good-quality routes within a limited amount of planning time. This problem also tends to be quite complex because the routes should be balanced: Several other competing objectives have to be taken into account by the driver such as driving time and energy consumption. Future many-core processing systems-on-chip are going to center around promising communication architectures like the Network on Chip (NoC)-that offer scalable, high-bandwidth communication links among embedded IP cores. The many-core NoC routing algorithm mixes deterministic routing with a locally adaptive strategy. CNNs are quite useful as convolutional layers of the processing unit used in image processing, pattern recognition, and computer vision applications. It is built like a stack of convolutional layers followed by down-sampling layers and then fully connected layers [12]. These are arrays of convolutional kernels, where each kernel convolved with the input data extracts local features.

Afterwards, a nonlinear block follows to enhance the model's capability and learn more complex data patterns. It forms a map for an input characteristic-that is, each neuron has connections to a local area of input data. Down-sampling layers are aimed at minimizing computation and parameters by lowering the resolution of the feature map. The last layer (fully connected) flattens the feature map in which every neuron in the layer is connected to all previous neurons. CNN output is a probability distribution of class labels. CNN has many advantages over traditional machine learning methods: it learns feature representation automatically from the input data rather than handcrafting features- robust to noise and distortion in input data. It requires a smaller number of parameters compared to fully connected networks because of weight sharing of each kernel across the feature map (i.e. local connectivity). CNN has been immensely successful in various applications, such as image classification, object detection, and face recognition. Wireless Sensor Networks Based on Multi-Criteria Clustering and Optimal Bio-Inspired Algorithm for Energy-Efficient Routing and the deep learning classifier, namely deep recurrent neural network classifier is used assign a real-valued review to each input twitter data thus, classifying the input data into two classes, such as positive review and negative review [15, 16].

A novel approach to enhancing the stability of Vehicular Ad Hoc Networks (VANETs) through a hybrid optimization technique that combines ensemble learning and metaheuristic algorithms. The authors, Gagan Preet Kour Marwah and Anuj Jain, analyze performance metrics such as delay, energy consumption, and throughput, demonstrating significant improvements over existing routing protocols. The study emphasizes the importance of adaptive routing in dynamic vehicular environments and provides valuable insights for researchers and practitioners in the field of intelligent transportation systems and network optimization [17].

6.1 Case Studies and Experiments

For the comprehensive assessment of the suggested DLP-Routing routing approach, a wide array of performance evaluations proved the most effective compared with the

Veins framework that simulates vehicle interactions on an 802.11p-based wireless network. The scenario used in the city traffic simulation is Taipei, with the four routing protocols simulated to compare performance against DLP-Routing, namely the Optimal Routing, Random Routing, ROP-UB Routing and RL Routing. Each simulation runs 800 s during which a certain number of fixed vehicles are deployed in one defined area of 4 km × 4 km, which are capable of putting up an VANET employing IEEE 802.11p transceivers. Different traffic input parameters that are being employed are vehicle density, speed, and cruising time.

The DLP-Routing algorithm is based on a deep neural network model, which is trained-offline using simulation data. The model by predicting the vehicle's state, network state, and destination node selects the optimal path using reinforcement learning techniques combined with DLP-Routing to allow the routing strategies to be trained online based on vehicle interactions in real-time. As far as traditional deep network models are concerned, multilayer models of deep neural networks boost the accuracy of the routing strategy, making them capable of effectively capturing this feature set space in a greater state space. These deep network models are based not only upon modeling individual vehicle routing strategies but also neighboring vehicle states are included to develop cooperative routing strategies [1, 4, 6].

6.2 Real-World Implementation of Deep Learning Route Planning

For example, an easy-to-use open-source solution for route planning based on deep learning and the runnable documentation of the said are still sought after for enhancing their salts this entry. The deep learning-based route planning solution proposed here has been introduced to implement in reality. The route planning system is operationalized by using the deep learning model that has been trained through the use of simulation. These include both the necessary files for offline training as well as the ones required for online planning to ease duplication. For the demonstration of the real-world use of the route planning system, two implementations are given in this application: one through Autonomous Vehicle Simulation Environment and the second through simulation games. Showing the very first instance, there is another avenue ahead as people opted to consider route planning to be a fundamental operation for numerous activities on vehicles, such as automation driving and V2V communication. Along with the upgrading of artificial intelligence, there comes the introduction of deep learning technologies.

This makes it possible for deep learning that uses neural networks in route planning to be introduced for driving more complex scenarios. Closure on route planning for test use with the two demonstrated use cases, AVSE and Gameworld. AVSE stands for Traffic Mix Simulation for Evaluating Opportunities in Automated Vehicle Technologies and V2V Networking, which can be used for various technologies related to automated driving vehicles and V2V networking. A straightforward small scenario is necessary. So, we set traffic lights on both sides, especially the terminals connected to cell ends. Both fixed and connected traffic lights with Deep Q Network models switched between them and build lightweight and accurate simulations.

6.3 Performance Evaluation and Comparison with Traditional Methods

Smart cities have indeed become lifelines concerning safety, comfort, and carrying conveniences with the aid of vehicular ad hoc networks (VANETs). Highly dynamic topologies in VANETs led to plenty of challenges in designing an efficient communication protocol. One major and imperative issue is route planning, the performance of data transmission being highly influenced by route planning in VANETs. In past years, there have been various heuristic routing algorithms, and they have been especially carved to support the enhancement of the packet delivery ratio (PDR) and equally reduce the delay in data transmission in VANETs. Deep learning (DL), being the new lion in the jungle at present, has found myriad applications in different fields, such as computer vision, natural language processing, and network security. Booming research in deep learning concerning wireless networks, as stated by Amalia et al. [4], provides the inspiration for the Fellowship. That is why a novel route planning algorithm which is based on deep learning has been conducted. For operating on each node, vehicle speed, direction, position, and timestamp information are utilized as inputs to a trained deep neural network (DNN) model to guess the expected global transmission delay to the destination node for all potential subsequent hop. Subsequently, the most probable next hop is found by minimizing the estimated delay. Therefore, two benefits are ascribable to the proposed deep learning route planning algorithm with respect to VANETs. First, the proposed approach achieves more accurate next hop selection in comparison with traditional heuristic-based route planning algorithms by employing a DNN model already trained to predict expected global transmission delays. Second, these processes avoid the expensive optimization of parameters in time-consuming ways found at the end of a DNN initiation time before being deployed with traditional heuristic methods [8]. Routing Protocols for Constraint Devices Internet of Things Network to improve the adhoc network using different protocols discussed [18].

6.4 Challenges and Future Directions

VANET stands for Vehicular Ad-hoc networks, where vehicles and roadside units (RSUs) facilitate communication between on-board units (OBUs) in one vehicle and OBUs in another vehicle. RSUs are stationary units whose location acts as both enablers to facilitate vehicle data aggregation and internet service provisioning to the vehicle. They are primarily used in creating a dedicated short-range communication (DSRC) environment for safety, city information, and cooperative system standards regarding intelligent transportation. Deployment of these units initially considers city topology and traffic flow, but several studies have shown that they have been very badly deployed and are underutilized [9].

The following steps to be implemented in the close future stand on designing deep learning-based route planning algorithms to exploit VANETs and RSUs to the best. Those algorithms proposed predicted the next best RSU from trajectory data as input and benchmarked with an ordinary OBU vehicle routing algorithm to assess the precision level. The prediction model is LSTM-based, and LSTM models with fully connected (FC) layers enable the bidirectional prediction. These models have considered city wise RSU networks, and one can find the introduction of this RSU network training into three different cities' networks and an aggregated dataset that provides vehicle diversity. 85% accuracy makes the results mostly overlap. It has potential to be generalized for other cities as well [8].

7 Challenges in Implementing Deep Learning in VANETs

There is a challenging scenario concerning how DL is rolled out in vehicular ad hoc network (VANETs) with respect to today's edge computing node problems for increases in the number of new algorithms and applications for the next generation. Edge nodes with DL capabilities face diverse tests in managing wireless modulation transitions during active link speeds and possible links disconnection, not to mention deterioration of quality of service (QoS) originating from various factors. A common occurrence in VANETs is that of link fading, which introduces time-variant loss and delay of all the data packets. This, therefore, means that data packets get lost whenever the link becomes hopped down, which would make the other edge nodes search for another path. It is expected that the deep neural network (DNN)-based routing paths will converge over time. There are also trade-offs in those scenarios: data transmission delays and learning with a DNN for path selection are most essential while keeping QoS provision on them. Further, looking at the previous paragraph it remains commendable to ignore the universal nature of the DNN, ensuring that it can easily recognize “similar” data but still has quality loss due to time-rate behavior. It was observed generally that models of DNNs required many epochs for training with the data. Eventually, such huge data must run to configure the weights of the model to generate valid learning outputs. Conversely, applying DNN models within very constrained and outlier data sets would not fulfill the universal minimum acceptance of loss criteria. Also, it is likely that time slots will be multiplied many times over to learn a good routing path during delay time related to QoS [2].

8 Future Directions

Going deeper and further into several methodological aspects of the very recent proposed method is necessary to see the improvement in efficiency in routing in VANETs. Maybe that is why only one model sometimes does not cater to all environments because, for the route plan generation, it is based on one model that continuously improves itself in all environments under the proposed continuous learning concept. Thus, to accommodate this DNN-RP for all types of applications, many research paths could be established or iterated, like deploying several DNN-RP models trained for various parameters, data sets, and configurations for different environments so the vehicles can choose from among them. Another way is to make a global model DNN-RP as a prototype, which has been pre-trained in a much wider and various dataset from different environments and scenarios so that it can be used as a basic model and then fine-tuned at each vehicle end locally with the specified data reducing the need for a large bandwidth. This method does not require data aggregation thus ensures better privacy of vehicle [9]. In our work, we had advocated the dependence on cross layers methodology for gathering, formulation and processing data in DNN-RP on the platform of the applications on the network layer of the vehicle. Suggesting as groundwork for further exploring paths in the narrow area to potentially broader intelligence DNN based model's deployment in other VANET applications, now and in the future, on those same layers or other newer layers of the OSI model stack, then, at the first creation, route planning intelligence is very much hoped to be enhanced.

9 Conclusion

The advancements in Deep Learning algorithms have been doing wonders across various major domains such as Image Processing and Natural Language Processing. Within the areas of application above, Neural Networks have been mostly exploited in housing a wide array of research and development works in the communication tier for vehicle-to-vehicle as well as vehicle-to-infrastructure networks. Neural Networks promise solutions that are hardware accelerated and thus require significantly lower computational times compared with actual computations. The text presented an overview of applicable potential applications of deep learning systems in routing, proactive prediction, and rein-formative learning. Experimental results obtained for the Vehicular Ad Hoc Networks-employing Deep Learning Techniques-demonstrated the improvement of performance as well as offering some new features compared to contemporary Routing Solutions of networks. There are multiple planned future directions of work: -the practical implementation of the models proposed using deep learning-specifically the next RL-and hardware acceleration for the Acceleration Systems. Current availability is found in the form of Embedded

Systems with higher characteristics, which support extensive deployment of the proposed routing algorithms in Real Life Scenarios.

References

1. ul Hassan, M., Al-Awady, A.A., Ali, A., Sifatullah, Akram, M., Munwar Iqbal, M., Khan, J., Ali Abdelrahman Ali, Y.: ANN-based intelligent secure routing protocol in vehicular ad hoc networks (VANETs) using enhanced AODV (2024)
2. AlSaqabi, Y., Krishnamachari, B.: Trip Planning for autonomous vehicles with wireless data transfer needs using reinforcement learning (2023)
3. Sumon, N.: Energy efficient route planning using VANET (2018)
4. Amalia, A., Pramitarini, Y., Hendra Yoga Perdana, R., Shim, K., An, B.: A deep-learning-based secure routing protocol to avoid blackhole attacks in VANETs † (2023)
5. Herbert Teixeira, L., Huszák, Á.: Reinforcement learning environment for advanced vehicular ad hoc networks communication systems (2022)
6. Nagaraj, U., Kadam, N.N.: Study of statistical models for route prediction algorithms in VANET (2011)
7. Goudarzi, S., Kama, M.N., Anisi, M.H., Soleymani, S.A., Doctor, F.: Self-organizing traffic flow prediction with an optimized deep belief network for internet of vehicles (2018)
8. Xu, C., Wang, S., Song, P., Li, K., Song, T.: Intelligent resource allocation for V2V communication with spectrum–energy efficiency maximization (2023)
9. Wang, L., Ye, H., Liang, L., Ye Li, G.: Learn to allocate resources in vehicular networks (2019)
10. Wang, X., Mavromatis, I., Tassi, A., Santos-Rodriguez, R., Piechocki, J.R.: Location anomalies detection for connected and autonomous vehicles (2019)
11. Sangaiah, A.K., Javadpour, A., Hsu, C.-C., Haldorai, A., Zeynivand, A.: Investigating routing in the VANET network: review and classification of approaches. Algorithms **16**, 381 (2023). https://doi.org/10.3390/a16080381
12. van Knippenberg, M., Holenderski, M., Menkovski, V.: Complex vehicle routing with memory augmented neural networks (2020)
13. Yang, C.P., Yen, C.E., Chang, I.C.: A software-defined directional Q-learning grid-based routing platform and its two-hop trajectory-based routing algorithm for vehicular ad hoc networks (2022)
14. Peyman, M., Fluechter, T., Panadero, J., Serrat, C., Xhafa, F., Juan, A.: Optimization of vehicular networks in smart cities: from agile optimization to learnheuristics and simheuristics (2023)
15. Vellaichamy, J., Basheer, S., Bai, P.S.M., Khan, M., Kumar Mathivanan, S., Jayagopal, P., Babu, J.C.: Wireless sensor networks based on multi-criteria clustering and optimal bio-inspired algorithm for energy-efficient routing. Appl. Sci. **13**, 2801 (2023). https://doi.org/10.3390/app13052801
16. Khan, M., Malviya, A.: Big data approach for sentiment analysis of twitter data using Hadoop framework and deep learning. In: 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE), Vellore, India, pp. 1–5 (2020). https://doi.org/10.1109/ic-ETITE47903.2020.201
17. Marwah, G.P.K., Jain, A.: A hybrid optimization with ensemble learning to ensure VANET network stability based on performance analysis. Sci. Rep. **12**, 10287 (2022). https://doi.org/10.1038/s41598-022-14255-1
18. Shahdad, S.Y., Khan, M., Sultana, H., Hussain, M.A., Meraj Bilfaqih, S.: Routing protocols for constraint devices Internet of Things network, In: 2019 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, pp. 0114–0117 (2019). https://doi.org/10.1109/ICCSP.2019.8697933

AI-Driven Security Mechanisms for IoT-Enabled VANETs

Bilal Ahmed, Arusa Kanwal, and Narmeen Shafqat

Abstract Vehicular Adhoc Networks (VANETs) are wireless communication networks that allow smart vehicles to communicate in real time. This communication can happen in multiple ways: Vehicle-to-Vehicle (V2V), where cars share information directly with each other, and Vehicle-to-Infrastructure (V2I), where vehicles connect with roadside systems like traffic lights. VANETs help improve road safety and traffic management. These networks utilize various Internet of Things (IoT) devices, including cameras, sensors and GPS modules to share real-time information with each other, such as location, speed and condition of the road. However, the increased connectivity comes with a greater exposure to cyber threats such as service disruption, identity spoofing, and manipulation of data, which can subsequently compromise the safety of the driver and the integrity of the network. Unfortunately, traditional security mechanisms are incapable of addressing evolving and context-specific cyber threats in VANETs. This chapter deals with an exploratory approach to how Artificial Intelligence (AI) can help counter these challenges through anomaly detection, attack prediction, and adaptive security measures. Integrating AI-driven security mechanisms into IoT-enabled VANETs can transform the transportation ecosystem, making it safer, smarter, and more resilient.

Keywords VANETs · AI · IoT · Connected vehicles · V2V · V2I

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1 Introduction

In today's era of smart cities and advanced transportation, vehicles are more connected than ever before. This connectivity is made possible through decentralized networks called Vehicular Adhoc Networks (VANETs). As depicted in Fig. 1, these networks allow vehicles to communicate with each other (Vehicle-to-Vehicle or V2V), with roadside infrastructure such as traffic lights and sensors (Vehicle-to-Infrastructure or V2I), and even with cloud-based systems that store and process this traffic data [1]. VANETs leverage wireless communication technologies such as Dedicated Short-Range Communications (DSRC) and IEEE 802.11p to enable reliable and low-latency communication [2]. This enables VANETs to significantly contribute to road safety by providing drivers and traffic management systems with timely alerts about potential dangers, such as nearby accidents, sudden braking of vehicles ahead, or hazardous road conditions like ice or fog. If an accident happens, vehicles in the area can automatically broadcast emergency signals, helping other drivers take precautions and allowing emergency services to respond faster. VANETs also improve traffic management by analyzing real-time traffic data and adjusting traffic signals based on congestion levels, and suggesting better routes to drivers. Ultimately, VANETs play a key role in building smarter, more sustainable cities by making transportation safer and more efficient.

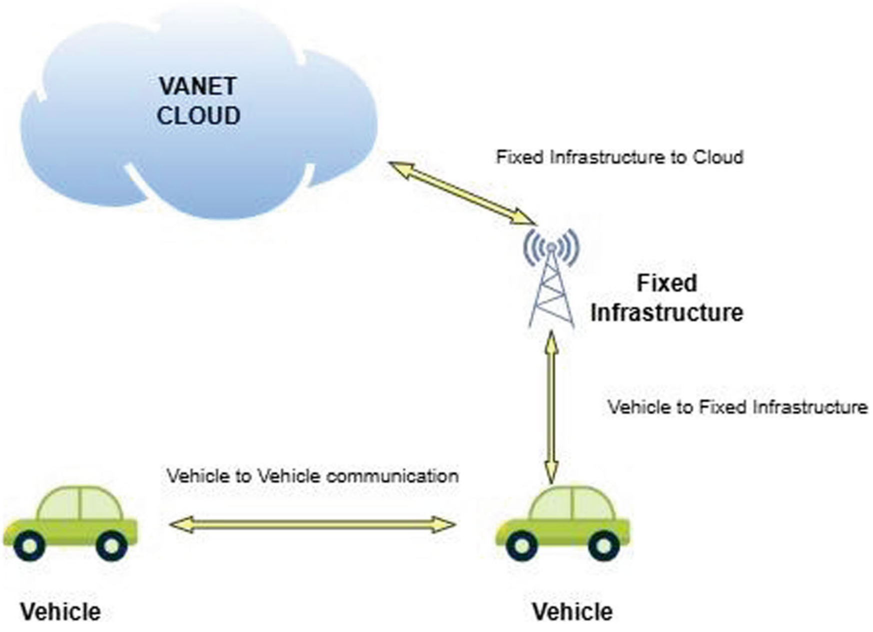
VANET CLOUD
Fixed Infrastructure to Cloud
Fixed Infrastructure
Vehicle to Fixed Infrastructure
Vehicle to Vehicle communication
Vehicle
Vehicle

Fig. 1 Typical communication modes in VANETs

Modern vehicles are increasingly equipped with multiple Internet of Things (IoT) devices, such as cameras, Light Detection And Ranging (LIDAR) sensors, and Global Positioning System (GPS) modules. These sensors further enhance the effectiveness of VANETs by providing advanced sensing, communication, and data analytics capabilities [3]. For instance, these devices help vehicles detect pedestrians, road signs, and obstacles more accurately, improving situational awareness. In addition, smart cameras and motion sensors can analyze driving behavior and detect unsafe practices such as sudden lane changes, speeding, or drowsy driving and timely alert the driver. IoT-based smart diagnostics can even detect mechanical issues (e.g., brake failure or low tire pressure) and alert the driver before critical failures occur. Moreover, the integrated IoT devices make traffic management smarter, as roadside infrastructure continuously collects and analyzes real-time traffic conditions to optimize traffic flow and enables better decision-making for drivers and traffic authorities. In essence, the combination of IoT and VANETs make transportation more intelligent and proactive [4].

For VANETs to function effectively, it is essential to ensure authentication and data confidentiality, integrity and reliability at all times [5]. However, as modern vehicles, especially self-driving cars, are extremely packed with sensors, communication modules, and smart systems, they also become more complex and vulnerable to cyberattacks. Adversaries can forge messages, disrupt services, or manipulate sensors, leading to potentially dangerous situations. For instance, an adversary could set up fake traffic signals or roadside infrastructure, misleading vehicles into unsafe routes. A real-world example of this is the Jeep Cherokee hack from 2015, where an attacker remotely took control of critical functions like steering and braking through the car's Uconnect system [6]. Such incidents highlight growing concerns, particularly for autonomous vehicles like Tesla's Autopilot, which rely heavily on V2V and V2I communication. As cars become smarter, it is not optional to secure these communication networks, but a necessity to ensure road safety.

Traditional security measures like encryption, firewalls, and real-time threat detection have been crucial in protecting VANETs from cyber threats. These methods work by securing data exchanges between vehicles and infrastructure, blocking unauthorized access, and detecting suspicious activity. However, as cybercriminals develop more advanced and unpredictable attack strategies, these conventional defenses struggle to keep up. This has led researchers to explore more adaptive, intelligent security approaches that can evolve alongside cyber threats. This is where Artificial Intelligence (AI) is proving to be a game-changer. Unlike traditional methods, AI can learn and adapt to new threats in real time, making it much more effective at detecting unusual behavior in a vehicle's network. By analyzing vast amounts of data, AI can spot anomalies, such as an adversary attempting to manipulate traffic signals or take control of a car, and respond instantly before any damage is done. AI-driven security can also predict potential attacks by recognizing patterns in cyber threats, allowing car manufacturers and cybersecurity researchers to stay one step ahead [7, 8].

The remainder of the chapter discusses the topological structure and architectural design of VANETs, the major cyber threats they face, and the current security measures in place. It also identifies existing gaps in these solutions and gives insights into how approaches driven by AI can tackle these challenges effectively.

2 Literature Survey

The following section outlines the infrastructure and communication modes of VANETs, offering insights into their operational characteristics and security requirements, and setting the stage for the subsequent sections.

2.1 VANETs Infrastructure

VANETs are a type of wireless network that allows vehicles to communicate without relying on fixed infrastructure [9]. They share similarities with Mobile Adhoc Networks (MANETs), which are self-organizing networks where mobile devices (nodes) communicate directly without needing mobile towers or base stations. However, unlike MANETs, VANETs are specifically designed for vehicle communication. Vehicles in VANETs act as mobile nodes, exchanging data through V2V or V2I communication modes [10].

2.1.1 Structural Layers of VANETs

As illustrated in Fig. 2, VANETs consist of two distinct layers: the top layer and the bottom layer, which together define the functionality of VANETs and enable communication between vehicles and roadside infrastructure.

The top layer consists of Trusted Authority (TA) which is trusted by all participants. It is equipped with robust computational capabilities and extensive storage capacity to manage the security and functionality of the entire system [11].

The bottom layer consists of On-Board Units (OBUs) and Roadside Units (RSUs). OBUs are communication devices installed in vehicles, enabling them to exchange data with other vehicles and infrastructure. RSUs are fixed units, such as traffic lights or road sensors, that help facilitate communication between vehicles and the network by collecting and transmitting important traffic and safety information [12] with OBUs using the DSRC protocol and with the TA through a secure wired channel [13]. The typical architecture of VANETs is illustrated in Fig. 3.

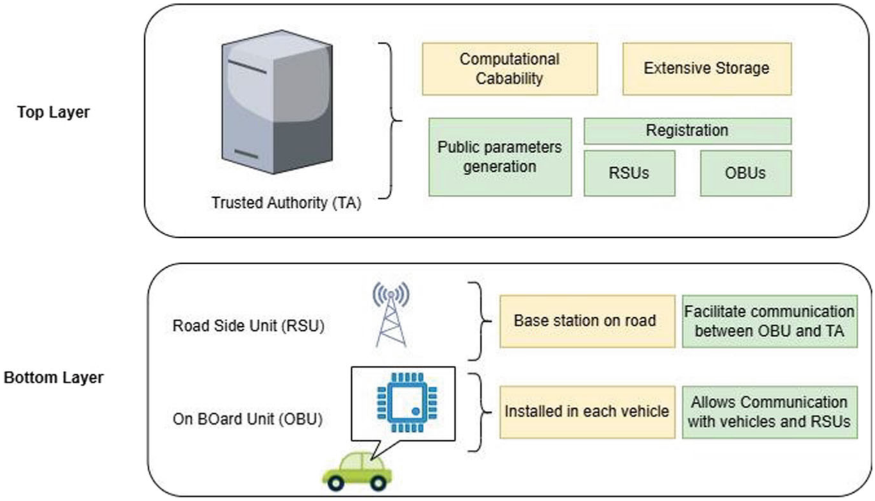
Top Layer
Trusted Authority (TA)
Computational Cabability
Extensive Storage
Public parameters generation
Registration
RSUs
OBUs
Bottom Layer
Road Side Unit (RSU)
Base station on road
Facilitate communication between OBU and TA
On BOard Unit (OBU)
Installed in each vehicle
Allows Communication with vehicles and RSUs

Fig. 2 Structural layers in VANETs

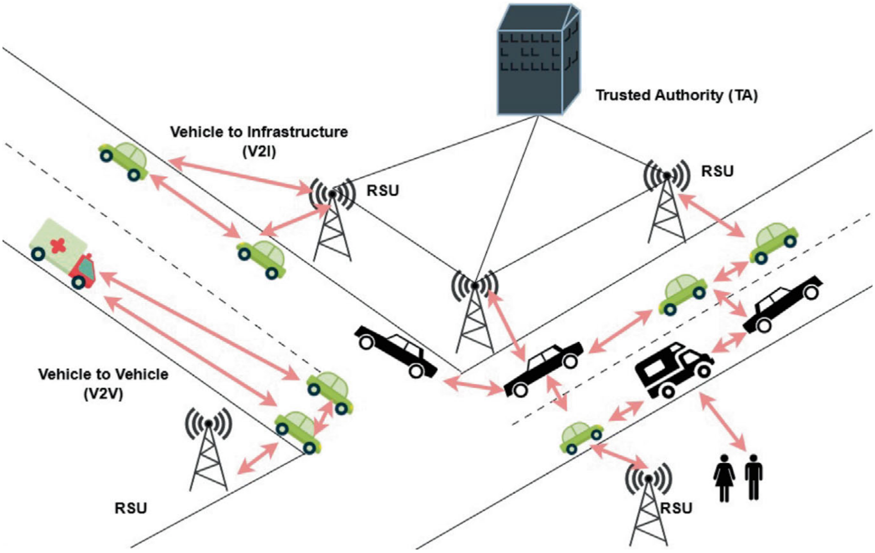
Trusted Authority (TA)
Vehicle to Infrastructure (V2I)
RSU
RSU
Vehicle to Vehicle (V2V)
RSU
RSU

Fig. 3 Typical architecture of VANETs

2.1.2 VANETs Communication Modes

VANETs support real-time communication between multiple entities using wireless communication technology. The primary communication modes in VANETs include:-

- **V2V**: Vehicles use onboard sensors to monitor their surroundings and communicate with nearby vehicles [14]. V2V communication links are used to exchange real-time information between vehicles regarding road conditions and other safety information messages to prevent collisions. [15].
- **V2I**: V2I communication links allow the vehicles to communicate with VANET infrastructure deployed on the road (e.g., RSUs, traffic signals). It provides access to the internet and other central services required for improved navigation and safety [16].
- **Infrastructure to Infrastructure (I2I)**: This facilitates communication between VANET infrastructure components, such as RSUs and traffic management centers, to share real-time traffic patterns and enhance overall system coordination [16].
- **Vehicle-to-Pedestrian (V2P)**: V2P links use mobile devices or wearable sensors to facilitate the exchange of information between vehicles and nearby pedestrians, thereby preventing road accidents and improving pedestrian safety [17].
- **Vehicle-to-Cloud (V2C)**: V2C links transmit data between the vehicles and cloud. This facilitates operations like big data analytics, decision making and predicting traffic congestion [18].

2.1.3 VANETs Communication Standards

For vehicles to communicate effectively, they utilize following specialized wireless communication standards that allow them to share real-time traffic and safety information, helping to prevent accidents and improve traffic flow [4].

- **IEEE 802.11p**: This is an extension of 802.11 Wi-Fi standard, specifically built for facilitating V2V and V2I communication by providing high throughput and low latency performance [19].
- **DSRC**: This wireless communication technology enables vehicles to share important safety and traffic information with each other and with roadside systems. The effective communication range of DSRC varies depending on the environment. In open highway settings, DSRC can maintain a strong connection over distances up to approximately 1219 m (about 0.75 miles). However, in urban areas, where buildings and other obstacles can interfere with signals, the effective communication range typically decreases to around 520 m (about 0.32 miles) [20].

2.2 VANETs Operational Characteristics

The following subsection outlines key operational characteristics that influence the performance and functionality of VANETs.

- **Mobility**: VANETs mobility is driven by vehicle movement along specific roadways, and constrained by traffic regulations. This dynamic mobility complicates the task of predicting network topology and the precise location of the vehicle [21].

With varying node speeds, from stationary RSUs to high-speed vehicles, communication reliability is also affected [22]. High mobility decreases transmission range, and moderate mobility leads to disruptions and latency [23, 24].
- **Network Size**: VANETs in dense areas, such as cities and highways, require robust communication systems to manage high vehicle and infrastructure density, particularly in traffic jams or accidents [25]. VANETs can cover vast areas, but increased data traffic and extended coverage raise challenges in maintaining reliable communication [26].
- **Safety**: VANETs enable safety applications by ensuring seamless communication between nodes like RSUs and OBUs, delivering timely information to prevent accidents and enhance road safety [27].
- **Network Coverage**: Network coverage varies with vehicle density. High-density areas improve connectivity and real-time application performance, while low-density areas risk fragmented networks and unreliable communications, impacting safety–critical services [16].
- **Power Resources**: Unlike a typical IoT setup, nodes in VANETs do not face power limitations, as OBUs are mostly powered by vehicle batteries, supporting continuous, resource-heavy tasks like cryptographic processing [28] and improving network coverage through the use of multiple antennas [29].

2.3 VANETs Security Characteristics

For smart vehicles, security is one of the stringent requirements to ensure the safety of the passengers and the surrounding environment [30]. Below we outline key security characteristics specific to VANETs that are essential for the smooth, secure, and efficient operation of VANETs, particularly in ensuring passenger safety, maintaining traffic management, and protecting privacy and data integrity.

2.3.1 Privacy

Drivers may hesitate while sharing details about their vehicles or intended destinations due to concerns about potential privacy violations [31]. Addressing these privacy challenges in VANETs demands balancing the protection of personal information while respecting individual privacy preferences.

2.3.2 Data Confidentiality

Protecting confidentiality entails safeguarding sensitive information concerning the vehicle and the driver against unauthorized access, thus preventing eavesdropping and unwanted tracking. Researchers have made use of symmetric encryption techniques like Advanced Encryption Standard (AES) for fast and efficient data protection, asymmetric techniques like Elliptic Curve Cryptography (ECC) for secure message exchange and sometimes hybrid encryption to enhance speed and reliability. Besides, Attribute-Based Encryption (ABE) restricts access to specific data based on user permissions [32] and differential privacy techniques introduce harmless noise into shared data, making it difficult for adversaries to extract meaningful information [33]. A key challenge in maintaining confidentiality in VANETs is ensuring that encryption does not introduce delays in real-time communication [34].

2.3.3 Data Integrity

Data integrity guarantees that messages are not altered in transit by any adversary. To this end, cryptographic hash functions, like MACs and digital signatures, are used to verify the integrity of the message [35]. Because of some real-time challenges, some recent research work explored lightweight integrity verifications like homomorphic hashing methods.

2.3.4 Network Availability

Availability ensures constant access to every resource on the network, not affected by existing vulnerabilities or by message flooding attacks. Cryptography techniques, accompanied by trust-based algorithms and protocols, are applied to protect the mentioned characteristic while ensuring the continuity of the resilience of the network [36].

2.3.5 Key Management

Securely managing the keys and revocation of expired or compromised keys is another critical characteristic of secure VANETs. An extendable number of nodes (i.e., vehicles) can result in a large set of keys requiring revocation, which increases the complexity and overhead associated with the revocation process [31].

2.3.6 Anonymity/Pseudonymity

The most prominent security feature in VANETs is pseudonymity. It conceals the identity of legitimate participants by hiding it, thus keeping their identity private. Legal entities do not use their actual information for communication but use a pseudonym for anonymous communication. Hence, this method preserves users' privacy and ensures that communication is safe and trustworthy within the network [37].

2.3.7 Node Authentication

The purpose of authentication is that only legitimate vehicles and legitimate infrastructure nodes should be able to participate in the communication within the VANET so that attacks targeting false data injection by malicious entities can be prevented. Authentication in VANETs can be classified into two types, namely Public Key Infrastructure (PKI) based and Identity (ID) based schemes. PKI refers to a security framework through which the communicators are authenticated with the aid of digital certificates and cryptographic key pairs. It demands a certification authority to assist in the management and issuance of these certificates alongside certificate verification [38]. In contrast, ID-based authentication does not use any certificates, but relies on a set of predefined identity information for verification, but suffers from key escrow and possible eavesdropping issues [39].

2.3.8 Non-repudiation

Non-repudiation, another crucial security characteristic in VANETs, ensures that the sender cannot deny generating a specific message. This characteristic links the content of a message directly to its originator, providing accountability and trust within the communication process [40].

2.3.9 Secure Location Validation

Location verification ensures accurate identification of node positions during communication. Implementing reliable mechanisms for location validation not only protects against potential attacks but also enhances the accuracy of the data validation process [37].

While these security characteristics are essential for ensuring the reliable and safe operation of VANETs, the following sections examine the various threats that VANETs face, highlighting the vulnerabilities that need to be addressed to maintain their security and functionality.

3 Threats and Current Mitigation Strategies in IoT-Enabled VANETs

IoT-enabled VANETs have the potential to completely transform transportation systems. However, the combination of wireless communication and IoT devices, the decentralized network architecture, and the open communication environment introduces many security risks in VANETs. Below, we explore these key threats and

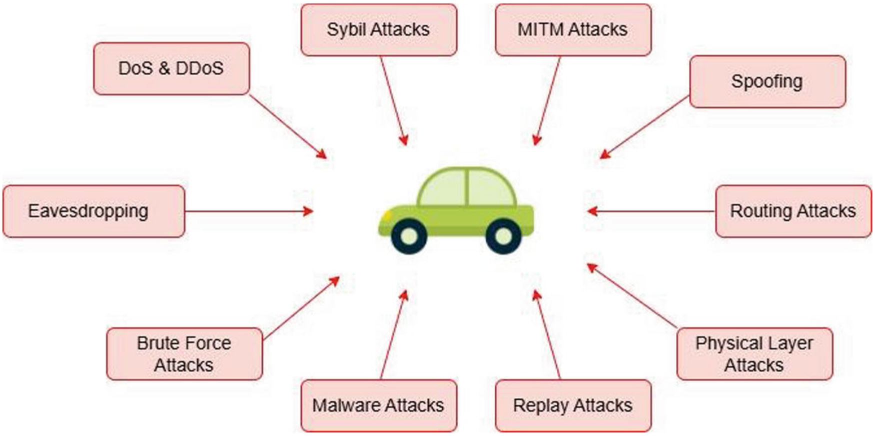

Fig. 4 Security threats to VANETs

the current mitigation strategies being employed to secure VANET infrastructure and operations. These threats are summarized in Fig. 4.

3.1 Eavesdropping and Data Interception

VANETs wireless communication channels are naturally prone to eavesdropping attacks, giving adversaries an edge to intercept private information including driver behaviour and vehicle whereabouts which could be exploited by unauthorized users to track and monitor vehicles [41]. An adversary can obtain unauthorized access to transmitted data by using technologies such as Software-Defined Radios (SDRs), which are programmable radio devices that can intercept and manipulate wireless communications. Mitigation measures include using modern encryption techniques, such as the AES to ensure data secrecy. Researchers have also introduced a new approach called Cryptography Mix-Zone (CMIX) which uses identity-based authentication to protect data confidentiality [42]. In CMIX, vehicles temporarily change their identities while passing through designated zones, thereby preventing unauthorized tracking and ensuring secure communication.

3.2 Denial-of-Service (DoS) and Distributed Denial-of-Service (DDoS) Attacks

A DoS attack is characterized by one source which sends unwanted and high volumes of traffic or non-valid requests in a manner that denies access to legitimate users in the network. A DDoS attack has several sources located at various different places and carry out their attack simultaneously with much increased force; therefore, such attacks are tougher to be prevented [43]. Such risks can be reduced using techniques like rate-limiting algorithms (that limit the number of data packets sent from a source within a specific time period) and Intrusion Detection Systems (IDS), which monitor and identify malicious activities in the network. Previous work has also proposed routing techniques, such as Secure and Efficient Adhoc Distance Vector (SEAD), which uses a one-way hash function [44] and a Dedicated Short-Range Communication (DSRC) based on-demand routing method [45], to prevent DoS attacks and ensure attackers cannot manipulate the routes of safe network nodes.

3.3 Sybil Attacks

In a Sybil attack, an adversary may break the trust and dependability by introducing various bogus identities in VANETs. These attacks have the potential to impair decision-making, interfere with communication, and cause routing errors. Digital certificates and PKI are two essential authentication methods for confirming the validity of network entities. If a malicious node is detected, its cryptographic keys are quickly revoked to limit damage [46]. However, deployment of PKI for VANETs is complex and requires careful management of keys and certificates. To detect Sybil attacks early, researchers have proposed Robust Sybil Attack Detection (RobSAD), a method that analyzes differences in how genuine and fake vehicles move. By identifying irregular motion patterns, RobSAD helps improve VANET security and ensures safer communication between vehicles [47].

3.4 Man-in-the-Middle (MITM) Attacks

MITM attacks happen when an adversary intercepts and modifies traffic between legal nodes. By inserting bogus data or changing messages, an adversary might create scenarios that misdirect vehicles or jeopardize safety. End-to-end encryption technologies like Transport Layer Security (TLS) can protect communication integrity and secrecy [48]. Prior work has demonstrated that effective user authentication also allows users to combine encryption and PKI to validate a batch of message signature pairs without a trusted identity [49].

3.5 Spoofing and Impersonation

Spoofing attacks occur when an adversary imitates genuine vehicles or infrastructure nodes on the VANET. For instance, the adversary may use GPS spoofing to mislead vehicles into the wrong route or dangerous conditions [50]. An adversary could alternatively impersonate a legitimate vehicle and send false traffic data to disrupt network traffic. To mitigate the possibility of spoofing, cryptographic authentication measures such as digital signatures and MAC should be used in verifying the legitimacy of the nodes and messages they broadcast. PKI should be used for vehicle-to-vehicle authentication [51], to sign messages for warnings [52] or to create group communications [53]. Authenticated Routing for Adhoc Networks (ARAN) was proposed as a solution in [54], which employs public key cryptography for authentication and timestamps to ensure the freshness and validity of the route. Another study enables vehicle authentication through regional Certificate Authorities (CAs) which are trusted entities responsible for issuing digital certificates. It uses dynamic anonymous keys (temporary keys that protect user identity) and short-lived certificates to enhance security and privacy [51]. In this way, only legitimate authorities can link a vehicle's Electronic License Plate to its alias, ensuring secure communication.

3.6 Routing Attacks

The goal of routing attacks is to interfere with VANETs' routing protocols, alter data pathways or divert traffic to hostile nodes, resulting in delays, data loss, or network isolation [41]. Message authentication and secure routing algorithms, including protected Adhoc On-demand Distance Vector (AODV), are two ways to secure the routing protocols and guarantee safe and appropriate data routing over the network. AODV is a routing protocol used to find the best path for data in adhoc networks. To defend against routing attacks, sensors and software are digitally signed. These problems are resolved in ARAN and SEAD routing protocols [55] by using cryptographic certificates, symmetric cryptography, and MAC and one-way hash functions. Moreover, an effective method Hop-by-hop Efficient Authentication Protocol (HEAP), based on AODV protocol, is suggested in [48] for protecting the network from routing attacks. It limits the distance travelled from the source to the destination using a geographical leash; if the threshold is exceeded, the packet is dropped. By increasing the trust between various nodes in VANETs, [56] offers some ways to improve security of various adhoc routing protocols.

3.7 Physical Layer Attacks

VANETs that depend on wireless communication are at risk from physical layer threats such as signal interference and jamming. An adversary can disrupt communication by sending a high-power signal on the same frequency in a jamming attempt. This can be especially problematic in safety–critical situations, such as emergency braking or accident avoidance. Countermeasures such as spread spectrum techniques and IDS are crucial to ensuring network resilience. Researchers suggest Frequency

Hopping, where the system rapidly switches between frequencies to avoid interference [57]. If an attack occurs, vehicles can also change their communication channel to restore connectivity. Another approach is to enable VANETs to switch between different wireless technologies, ensuring uninterrupted communication even if one channel is compromised [58].

3.8 Replay Attacks

A replay attack occurs when an adversary intercepts and resends previously transmitted network data to trick a system into thinking it's communicating with a legitimate user. By exploiting weaknesses in the authentication process, the adversary can impersonate a trusted vehicle or server, gaining unauthorized access to sensitive information. This can allow them to manipulate communication, disrupt services, or even take control of certain network functions. To prevent replay attacks in vehicular networks, network-wide synchronized time and nonces (timestamps) can be used to detect outdated messages [59]. The most effective defense is verifying received data against multiple trusted sources, ensuring responses are based on accurate and current information [60].

3.9 Malware Attacks

An adversary transmits malicious or spam messages across the network, thereby utilizing network bandwidth and increasing transmission latency. Because of the absence of centralized administration and the required infrastructure, this type of attack is challenging to control. For example, adversaries may send spam or malicious messages to a group of users. While users might ignore these messages, similar to how they disregard advertisements, the sheer volume of unwanted data can still slow down communication, disrupt network performance, and create security vulnerabilities within the system. Using trustworthy hardware prevents unauthorized nodes from changing current protocols and settings [61].

3.10 Brute Force Attacks

Brute force attacks on VANETs involve repeatedly guessing encryption keys or authentication credentials to gain unauthorized access to the network [62]. Langley et al., have proposed an authentication solution [63] that combines a vehicle's unique identity number with a long timestamp, hashing them together to enhance security.

4 Security Gaps in IoT-Enabled VANETs

Even while currently employed mitigation methods provide reasonable protection from certain threats faced by IoT-enabled VANETs, some loopholes cannot be avoided as these techniques often grapple with scalability, adaptability, and the dynamically changing characteristics of VANETs. The subsequent section elaborates on these limitations and areas for potential improvements in providing safety designs for VANETs.

4.1 Gaps in Threat Intelligence Sharing

Effective threat intelligence sharing is critical for recognizing and mitigating emerging threats in IoT-enabled VANETs. However, the absence of defined protocols and the inability to process threat intelligence data in real-time limit the flow of critical security information. As a result, VANETs may struggle to use collective knowledge to adaptively fight against coordinated attacks. To bridge these gaps and improve VANET system security, standardized and real-time threat intelligence exchange mechanisms must be developed. In addition, the volume of data created by IoT devices in VANETs requires real-time analysis in order to detect new hazards quickly. However, many present systems cannot handle this data rapidly enough, resulting in delayed responses. Therefore, authors of [64] investigate and suggest the requirement for real-time context-based threat detection in VANETs.

4.2 Inadequate Trust Management in Dynamic, Decentralized Environments

Trust management is an important aspect of ensuring secure communication between vehicles and infrastructure in IoT-enabled VANETs. However, trust is hard to maintain because these networks are highly dynamic and decentralized. In contrast to traditional systems with a central authority, VANETs rely on peer-to-peer interactions, which makes them vulnerable to malicious node behavior and data manipulation. Vehicles often encounter unknown nodes, making it hard to verify the reliability of shared information. With no centralized authority for trust, the network faces the risk of accepting false or misleading data by increased complexity in security. Prior work has proposed a decentralized trust management system [65] which builds and assesses trust by observing the behavior and interaction amongst nodes within the network, thereby eliminating the requirement for a central authority. One study has also explored the use of blockchain in VANETs for a decentralized and tamper-proof way of trust management [66].

4.3 Vulnerable Communication Protocols in Dynamic Environments

As discussed before, IoT-enabled VANETs are exposed to security threats in dynamic environments due to their decentralized nature and high mobility. Most of the currently used protocols, like TLS, offer strong encryption; however, they are not considered suitable for high-mobility low-latency vehicular networks. To enhance security in smart cities, Sumit et al. [67] propose a dynamic routing strategy that leverages an optimized chaotic secure multi-verse optimization algorithm, improving secure data transmission in VANETs [67]. In addition, Gupta et al. [68] introduced an authentication-based secure data dissemination framework for 5G-based vehicular communications to tackle these security challenges.

4.4 Insufficient Privacy Protection Mechanisms

Lack of privacy protection mechanisms in IoT-enabled VANETs coupled with frequent information sharing leads to privacy violations like location tracking, unauthorized data access, and identity disclosure [69]. Emerging privacy-preserving solutions include blockchain-enabled identity management systems for improving privacy in VANET clouds. This approach uses the decentralized characteristic of blockchain for protecting user identities and data transactions, thereby minimizing the risks associated with centralized data storage [70]. However, privacy protection solutions are still weak, and need further development as these measures fail to efficiently adapt to the ever-changing topology and real-time communication needs of VANETs. Hence, the scope for the continued research is to formulate adaptable and scalable privacy-enhancing technologies that will find acceptance in the dynamic contexts of IoT-enabled VANETs.

4.5 Deficiencies in Intrusion Detection and Threat Response Systems (IDTRS)

IoT-enabled VANETs pose significant network security threats due to weaknesses in IDTRS. These systems seek to identify and counter illicit access, malware, and other anomalies in static environments. However, because of their inability to handle the high mobility and dynamic nature associated with VANETs, they often fail to recognize or respond to threats in real-time. In addition, VANETs decentralized topology complicates efforts to monitor network traffic and identify malicious activity. Scaling issues are caused by the ever-increasing numbers of interconnected autos and IoT devices. Traditional systems might be overwhelmed in computation and storage resulting in performance drop and increased susceptibility [71]. From the adversary's perspective, advanced machine-learning techniques are routinely used to mimic legitimate behaviors to evade those IDSs. The current gap in detection capabilities underlies the urgent demand for next-generation IDS solutions that integrate real-time behavioral analytics and collaborative threat detection mechanisms to increase efficacy against emerging threats.

5 AI-Driven Security Mechanisms in IoT-Enabled VANETs

To tackle aforementioned challenges, we need smarter solutions that can keep up with the constantly changing nature of VANETs. This subsection highlights using AI as a promising solution to quickly detect threats, manage trust between vehicles, and protect user privacy.

5.1 AI for Intrusion Detection and Anomaly Detection

The dynamic and decentralized nature of VANETs leaves traditional IDS with limited capability to identify sophisticated, multidimensional attacks. AI-based IDS use Machine Learning (ML) to learn from network traffic and detect deviations from standard behavior, allowing them to adapt to changing threats.

Typically, known attacks are detected using Supervised Learning methods [72], such as Random Forest and K-Nearest Neighbors (KNN) that make use of labeled data. In simple words, supervised learning trains a model using pre-classified data in order to recognize similar patterns in newly presented data. Random Forest technique enhances the accuracy by combining the features of many decision trees to make the final classification, whereas KNN classifies a new data point based on its similarity to existing classified points. Hence, such models can analyze network traffic and help detect known malicious activities such as spoofing and DOS attacks.

In contrast, unknown or unseen threats can be identified with unsupervised learning techniques such as K-means clustering. Unlike supervised learning, unsupervised methods work with no labeled data and are geared toward the identification of hidden patterns or anomalies. Specifically, K-means clustering groups similar data points, making it useful for detecting unusual network traffic that deviates from normal behavior. Besides, hybrid models [73] combine supervised and unsupervised learning to improve detection accuracy for both known and unknown attacks, with reduced false positives.

In addition, Reinforcement Learning (RL) enables the IDS to alter detection strategies on the run. RL works by continuously learning from interactions with the network environment, optimizing responses to new and evolving threats without needing predefined labels. In essence, with the help of AI, VANET security systems can proactively identify and eliminate cyber-attacks before any damage is done.

5.2 AI for Trust Management

VANETs are extremely decentralized and highly mobile networks; therefore, incorporating AI would strengthen the trust management in such networks. Traditional reputation-based systems [74] fail to effectively handle the dynamic nature of VANETs since they are based on static models and insufficient data. AI techniques can easily get around these limitations by providing real-time behavioral assessment of the nodes resulting in a timely and more precise approach to trust management. Depending on different criteria to source their judgment on reliability, AI models can apply regression, classification, and clustering. Based on past interactions, regression [75] would predict future behaviour, classification would label nodes capable of malicious versus trustworthy behaviour under their history, and clustering would join nodes into groups according to similar parameter sets of characteristics.

Moreover, context-aware trust models [76] come in handy inside VANETs, which are dependent on highly dynamic contingents such as traffic conditions, environmental circumstances, and node mobility. The AI model correlates the trust level with the real-time input variables, ensuring that decision-making about node interactions remains relevant and accurate under dynamically changing conditions. In the case whereby a vehicle suffers repeated traffic accidents or behaves erratically following environmental circumstances like the state of the road, the trust give-up behaviour can be adjusted by the AI. Unlike static evaluation scenarios, this dynamic trust management will have a solid impact on the security, risk mitigation, and effective communication across nodes in a VANET system from adversaries' interruptions.

5.3 AI for Privacy Protection

Privacy protection in IoT-enabled VANETs is crucial since the data transferred is sensitive, including vehicle positions, speed, and driver behaviour. AI enhances privacy security by preventing breaches while ensuring the efficiency of VANET services. AI reliably attaches differential privacy [77] to VANETs, thereby ensuring that the privacy of individual vehicles is preserved even if data is shared for safety or traffic management purposes. The differential privacy mechanism allows system analysts to extract useful information from the mechanisms while retaining the anonymity of the particular person or vehicle within the data set by carefully introducing noise in the data. AI algorithms can apply differential privacy to sensitive vehicle data, such as speed and location, to ensure these attributes cannot be linked with specific individuals or vehicles. The protected private information can allow the system or authorities to perform tasks like accident prediction or traffic optimization.

Driver behaviour and vehicle trajectories can also be efficiently masked in AI-protected systems [78]. AI models can automatically identify sensitive components of a data stream and use tools like encryption or pseudonymization to protect privacy.

Pseudonymization involves replacing identifying information, like a vehicle's registration number or driver's name, with an artificial identifier, such as a random number or pseudonym. AI may hide location information by, for example, slightly moving a vehicle, such that its precise path is not tracked; meanwhile, these systems are still able to perform essential functions like congestion management and routing.

5.4 AI for Secure Communication Protocols

In VANETs, secured data transmission becomes essential as communication pathways come under threat from eavesdropping, DoS, and MITM attacks. Traditional cryptographic mechanisms may be effective in many cases, but they are usually never adequate to satisfy the high mobility and latency demands of VANETs since they do not dynamically adapt to the fast-changing conditions of the network. AI can guarantee the generation of reliable communication protocols and secure data transmission in real time. Additionally, AI can adaptively enhance current encryption methods [79] by altering encryption parameters based on real-time conditions and threats. For instance, AI could decide to raise the levels of encryption in areas that are experiencing high traffic attacks or simply switch to an entirely different encryption algorithm with a much higher security level.

The AI-powered routing protocols [80] enhance the security of the transmitted data by dynamically choosing the safest paths for transmission. These protocols hence change through self-adaptation and adjustments for the dynamic conditions that affect network topology and conditions for ongoing traffic, and data is prevented from malicious entities or compromised nodes. For example, an AI algorithm can recognize strange behavior and detect a vehicle or infrastructure node that is compromised and reroute the data immediately via the more secure path to minimize cyber threats.

5.5 AI for Attack Prediction and Prevention

Using predictive models [81] trained on previous attack data, AI can spot trends indicating new dangers before they worsen, allowing for timely intervention. DDoS attacks, for instance, might be predicted by looking at traffic patterns for unusual request spikes, which are a prevalent characteristic of these attacks. The AI system can monitor traffic on the network, track its volume and frequency, and even detect anomalies that may signal a potential DDoS attack. Preventive measures may thus be initiated once detected, such as slowing traffic or isolating the attacked nodes. Once a routing disruption is observed in the patterns detected in the changes of the routing table and anomalous route-pathing, AI can take preventive measures by rerouting any traffic or isolating the vulnerable path for safe communication. In this way, AI remains a very good tool that boosts network reliability and secures data flows against several types of attacks on VANETs.

5.6 AI for Real-Time Threat Response

A real-time threat response by AI is important to defend against threats to VANETs, especially when such threats become changeable and adaptive. Early threat detection along with autonomous responses ensures safe network operation even after an attack. In the event of a MITM attack [82], AI can immediately reroute traffic or impose stronger encryption to avoid data interception or manipulation. By continuously analyzing attack patterns in real-time, AI adapts security protocols on the fly, such as implementing TLS encryption or VPN tunnels to safeguard data integrity and confidentiality. With its ability to monitor network activity and assess risks in real-time, AI minimizes potential damage and keeps vehicular communication secure. Besides this, the incorporation of RL [83] would allow the continuous improvement of AI systems, as RL-based systems can learn from successes and failures in previous attacks and fine-tune their response strategies to offer more effective attack responses in the future. AI ensures that VANETs are not only proactively protected, but also capable of real-time response against potential threats.

5.7 Federated Learning for Privacy-Preserving Security

One of the challenges in implementing AI into IoT-enabled VANETs is protecting privacy. Federated learning promises to address this by enabling learning across various decentralized devices without requiring the sharing of private data. This approach thus maintains an individual vehicle's and user's privacy yet allows the AI system to learn from a vast and varied dataset [78]. It thus allows for collaborative learning while making sure of confidentiality for the sensitive data within each device, lowering the risk of data exposure and maintaining compliance with the privacy requirements.

In essence, the use of AI can lead to a significant improvement in IoT-enabled VANETs (as shown in Fig. 5). AI can improve communication through optimized link management, data congestion, and routing by predicting traffic flow patterns. AI can also enhance immediate detection of accidents by analyzing real-time sensor data and predicting hazards to assist in road safety by providing collision alerts. Finally, AI can deal with traffic management through pattern recognition and real-time decision-making to allow for intelligent traffic routing, scheduling, and monitoring so that road safety and efficiency are increased.

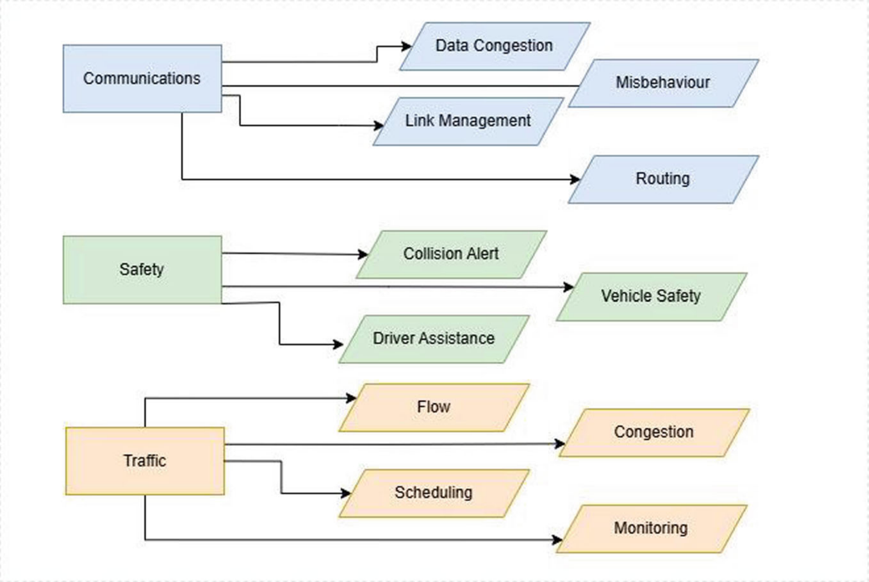
Communications
Data Congestion
Misbehaviour
Link Management
Routing
Safety
Collision Alert
Vehicle Safety
Driver Assistance
Flow
Traffic
Congestion
Scheduling
Monitoring

Fig. 5 AI improving communication, road safety and traffic management in VANETs

6 Challenges and Future Directions

Even in AI-enabled IoT systems, the decentralized and dynamic nature of VANETs presents challenges. In addition, the mobility of nodes leads to constantly changing network topologies, complicating the management and establishment of stable security frameworks. In that line, further research endeavors should focus on the future development of adaptive lightweight algorithms that can handle the dynamic characteristics of VANETs. In this case, developing models will include using various techniques, such as model pruning, quantization, and knowledge distillation, that aim to improve AI systems through performance and scale for these increasingly dynamic topologies. Another prominent solution is edge computing, which will enable AI tasks to be performed close to the data sources. It will also drastically reduce latency for real-time threat detection and enhance overall network security. Additionally, delivering 5G as well as 6G technologies will be critical for ultra-low latency, high-speed communication, and network slicing, which will prioritize critical system-related data and support the seamless operation of VANETs. Finally, by engaging both network instabilities and swift changes in topology, any AI-driven security frameworks can provide reliable stability, efficiency, and scalability to VANETs and offer them greater resilience against emerging cyber threats.

7 Conclusion

Integrating AI with the IoT-based VANET is potentially going to greatly enhance both the security and efficiency of transportation systems in the near future. Contrary to conventional security mechanisms, AI-based systems, like intrusion detection, real-time threat mitigation, and protection of privacy, provide adaptive as well as proactive defense. Its ability to identify evolving threats and optimize communication protocols to prevent attacks in real-time makes it an effective means to counter cyber risks in VANETs. As the technology of AI advances, standardization of security protocols will be very important in ensuring that VANETs operate smoothly and securely, paving the way for safer, smarter, and more resilient transportation networks.

References

1. Kumar, V., Mishra, S., Chand, N.: Applications of VANETs: present & future. Commun. Netw. **05**, 12–15 (2013). https://doi.org/10.4236/cn.2013.51B004
2. Liang, W., Li, Z., Zhang, H., Wang, S., Bie, R.: Vehicular adhoc networks: architectures, research issues, methodologies, challenges, and trends. Int. J. Distrib. Sens. Netw. **11**, 745303 (2015). https://doi.org/10.1155/2015/745303
3. Parekh, D., Poddar, N., Rajpurkar, A., Chahal, M., Kumar, N., Joshi, G.P., Cho, W.: A review on autonomous vehicles: progress, methods and challenges. Electronics **11**(14), 2162 (2022)
4. Ignatious, H.A., Khan, M.: An overview of sensors in autonomous vehicles. Proc. Comp. Sci. **1**(198), 736–741 (2022)
5. Sheikh, M.S., Liang, J.: A comprehensive survey on VANET security services in traffic management system. Wirel. Commun. Mob. Comput. **2019**, 2423915 (2019). https://doi.org/10.1155/2019/2423915
6. Erwin, B.: The groundbreaking 2015 Jeep hack changed automotive cybersecurity. Fractional CISO (2021). Available Online at https://fractionalciso.com/the-groundbreaking-2015-jeep-hack-changed-automotive-cybersecurity/
7. Nandy, T., Noor, R.M., Kolandaisamy, R., Idris, M.Y., Bhattacharyya, S.: A review of security attacks and intrusion detection in the vehicular networks. J. King Saud Univ. Comp. Inf. Sci. **1**, 101945 (2024)
8. Saoud, B., Shayea, I., Yahya, A.E., Shamsan, Z.A., Alhammadi, A., Alawad, M.A., Alkhrijah, Y.: Artificial Intelligence, Internet of things and 6G methodologies in the context of Vehicular Adhoc Networks (VANETs): survey. ICT Express (2024)
9. Fotros, M., Rezazadeh, J., Sianaki, O.A.: A survey on vanets routing protocols for iot intelligent transportation systems. In: Workshops of the International Conference on Advanced Information Networking and Applications, pp. 1097–1115 (2020)
10. Al-Shareeda, M.A., Anbar, M., Alazzawi, M.A., Manickam, S., Al-Hiti, A.S.: Lswbvm: a lightweight security without using batch verification method scheme for a vehicle Adhoc network. IEEE Access **8**, 170507–170518 (2020)
11. Shladover, S.E.: Connected and automated vehicle systems: introduction and overview. J. Intell. Transp. Syst. **22**(3), 190–200 (2018)
12. Al Shareeda, M., Khalil, A., Fahs, W.: Towards the optimization of road side unit placement using genetic algorithms. In: 2018 International Arab Conference on Information Technology (ACIT), pp. 1–5. IEEE (2018)
13. Yang, X., Yi, X., Khalil, I., Zeng, Y., Huang, X., Nepal, S., Yang, X., Cui, H.: A lightweight authentication scheme for vehicular adhoc networks based on MSR. Veh. Commun. **1**(15), 16–27 (2019)

14. Özdemir, Ö., Kılıç, İ, Yazıcı, A., Özkan, K.: A V2V system module for inter vehicle communication. Appl. Mech. Mater. **8**(850), 16–22 (2016)
15. Sliwa, B., Falkenberg, R., Liebig, T., Piatkowski, N., Wietfeld, C.: Boosting vehicle-to-cloud communication by machine learning-enabled context prediction. IEEE Trans. Intell. Transp. Syst. **21**(8), 3497–3512 (2019)
16. Zemrane, H., Baddi, Y., Hasbi, A.: Mobile adhoc networks for intelligent transportation systems: comparative analysis of the routing protocols. Procedia Comp. Sci. **1**(160), 758–765 (2019)
17. Li, X., Zhou, R., Zhang, Y.J., Jiao, L., Li, Z.: Smart vehicular communication via 5G mm waves. Comput. Netw. **8**(172), 107173 (2020)
18. De Almeida, T.T., Ribeiro Júnior, J.G., Campista, M.E., Costa, L.H.: Wi-fi direct performance evaluation for v2p communications. J. Sens. Actuator Netw. **9**(2), 28 (2020)
19. Ahmed, S.A., Ariffin, S.H., Fisal, N.: Overview of wireless access in vehicular environment (WAVE) protocols and standards. Environment **7**(8) (2013)
20. Bae, J.K., Park, M.C., Yang, E.J., Seo, D.W.: Implementation and performance evaluation for DSRC-based vehicular communication system. IEEE Access. **14**(9), 6878–6887 (2020)
21. Toor, Y., Muhlethaler, P., Laouiti, A., De La Fortelle, A.: Vehicle adhoc networks: applications and related technical issues. IEEE Commun. Surv. Tutorials **10**(3), 74–88 (2008)
22. Ullah, A., Yao, X., Shaheen, S., Ning, H.: Advances in position based routing towards its enabled fog-oriented vanet–a survey. IEEE Trans. Intell. Transp. Syst. **21**(2), 828–840 (2019)
23. Sharef, B.T., Alsaqour, R.A., Ismail, M.: Vehicular communication Adhoc routing protocols: a survey. J. Netw. Comput. Appl. **1**(40), 363–396 (2014)
24. Goli-Bidgoli, S., Movahhedinia, N.: Towards ensuring reliability of vehicular adhoc networks using relay selection techniques and D2D communications in 5G networks. Wireless Pers. Commun. **114**(3), 2755–2767 (2020)
25. Hussein, N.H., Koh, S.P., Yaw, C.T., Tiong, S.K., Benedict, F., Yusaf, T., Kadirgama, K., Hong, T.C.: SDN-based VANET routing: a comprehensive survey on architectures, protocols, analysis, and future challenges. IEEE Access (2024)
26. Nyangaresi, V.O., Rodrigues, A.J., Taha, N.K.: Mutual authentication protocol for secure VANET data exchanges. In: International Conference on Future Access Enablers of Ubiquitous and Intelligent Infrastructures, pp. 58–76. Springer International Publishing, Cham (2021)
27. Al-shareeda, M.A., Alazzawi, M.A., Anbar, M., Manickam, S., Al-Ani, A.K.: A comprehensive survey on vehicular adhoc networks (VANETs). In: 2021 International Conference on Advanced Computer Applications (ACA), pp. 156–160. IEEE (2021)
28. Rashid, S.A., Audah, L., Hamdi, M.M., Abood, M.S., Alani, S.: Reliable and efficient data dissemination scheme in VANET: a review. Int. J. Electr. Comp. Eng. (IJECE). **10**(6), 6423–6434 (2020)
29. Boussoufa-Lahlah, S., Semchedine, F., Bouallouche-Medjkoune, L.: Geographic routing protocols for Vehicular adhoc NETworks (VANETs): a survey. Veh. Commun. **1**(11), 20–31 (2018)
30. Obaidat, M., Khodjaeva, M., Holst, J., Ben Zid, M.: Security and privacy challenges in vehicular adhoc networks. In: Connected Vehicles in the Internet of Things: Concepts, Technologies and Frameworks for the IoV, pp. 223–251 (2020)
31. Ishtiaq, M., Anwar, S., Shah, M.A.: A survey on secure routing strategies in VANETs. In: 2019 25th International Conference on Automation and Computing (ICAC), pp. 1–6. IEEE (2019)
32. Tang, F., Kawamoto, Y., Kato, N., Liu, J.: Future intelligent and secure vehicular network toward 6G: machine-learning approaches. Proc. IEEE **108**(2), 292–307 (2019)
33. Kumar, A., Bansal, M.: A review on VANET security attacks and their countermeasures. In: 2017 4th International Conference on Signal Processing, Computing and Control (ISPCC), pp. 580–585. IEEE (2017)
34. Günay, F.B., Öztürk, E., Çavdar, T., Hanay, Y.S., Khan, A.U.: Vehicular adhoc network (VANET) localization techniques: a survey. Arch. Comput. Methods Eng. **28**, 3001–3033 (2021)

35. Caballero-Gil, P., Wang, X.: Security issues in vehicular adhoc networks. Mobile Adhoc Netw: Appl. **30**, 67–88 (2011)
36. Agarwal, P.: Technical review on different applications, challenges and security in VANET. J. Multimedia Technol. Recent Advancements. **4**(3), 21–30 (2017)
37. Zhong, H., Han, S., Cui, J., Zhang, J., Xu, Y.: Privacy-preserving authentication scheme with full aggregation in VANET. Inf. Sci. **1**(476), 211–221 (2019)
38. Sheikh, M.S., Liang, J., Wang, W.: Security and privacy in vehicular adhoc network and vehicle cloud computing: a survey. Wirel. Commun. Mobile Comput.
39. Horng, S.J., Tzeng, S.F., Huang, P.H., Wang, X., Li, T., Khan, M.K.: An efficient certificateless aggregate signature with conditional privacy-preserving for vehicular sensor networks. Inf. Sci. **1**(317), 48–66 (2015)
40. Tripathi, V.K., Venkaeswari, S.: Secure communication with privacy preservation in VANET-using multilingual translation. In: 2015 Global Conference on Communication Technologies (GCCT), pp. 125–127. IEEE (2015)
41. Sheikh, M.S., Liang, J., Wang, W.: A survey of security services, attacks, and applications for vehicular Adhoc networks (VANETs). Sensors. **19**(16), 3589 (2019)
42. Zhang, L.: OTIBAAGKA: a new security tool for cryptographic mix-zone establishment in vehicular Adhoc networks. IEEE Trans. Inf. Forensics Secur. **12**(12), 2998–3010 (2017)
43. Zeadally, S., Hunt, R., Chen, Y.S., Irwin, A., Hassan, A.: Vehicular Adhoc networks (VANETS): status, results, and challenges. telecommunication systems. **50**, 217–241 (2012)
44. Hu, Y.C., Johnson, D.B., Perrig, A.: SEAD: secure efficient distance vector routing for mobile wireless Adhoc networks. Adhoc Netw. **1**(1), 175–192 (2003)
45. Hu, Y.C., Perrig, A., Johnson, D.B.: Ariadne: A secure on-demand routing protocol for Adhoc networks. In: Proceedings of the 8th Annual International Conference on Mobile Computing and Networking, pp. 12–23 (2002)
46. Raya, M., Papadimitratos, P., Hubaux, J.P.: Securing vehicular communications. IEEE Wirel. Commun. **13**(5), 8–15 (2006)
47. Chen, C., Wang, X., Han, W., Zang, B.: A robust detection of the sybil attack in urban vanets. In: 2009 29th IEEE International Conference on Distributed Computing Systems Workshops, pp. 270–276. IEEE (2009)
48. La, V.H., Cavalli, A.R.: Security attacks and solutions in vehicular Adhoc networks: a survey. Int. J. AdHoc Netw. Syst. (IJANS). **4**(2), 1–20 (2014)
49. Raiya, R., Gandhi, S.: Survey of various security techniques in VANET. Int. J. Adv. Res. Comp. Sci. Softw. Eng. **4**(6), 431–433 (2014)
50. Wen, H., Huang, P.Y., Dyer, J., Archinal, A., Fagan, J.: Countermeasures for GPS signal spoofing. In: Proceedings of the 18th international technical meeting of the satellite division of the institute of navigation (ION GNSS 2005), pp. 1285–1290 (2005)
51. Rajadurai, R., Jayalakshmi, N.: Vehicular network: properties, structure, challenges, solutions for improving scalability and security.
52. Blum, J., Eskandarian, A.: The threat of intelligent collisions. IT Prof. **6**(1), 24–29 (2004)
53. Vèque, V., Johnen, C.: Hiérarchisation dans les réseaux Adhoc de véhicules. In: 8èmes journées francophones Mobilité et Ubiquité, UBIMOB, pp. 45–52. CEPADUES (2012)
54. Sanzgiri, K., Dahill, B., Levine, B.N., Shields, C., Belding-Royer, E.M.: A secure routing protocol for Adhoc networks. In: 10th IEEE International Conference on Network Protocols, Proceedings, pp. 78–87. IEEE (2002)
55. Raw, R.S., Kumar, M., Singh, N.: Security challenges, issues and their solutions for VANET. Int. J. Netw. Secur. Appl. **5**(5), 95 (2013)
56. Patel, N.J., Jhaveri, R.H.: Trust based approaches for secure routing in VANET: a survey. Procedia Comp. Sci. **1**(45), 592–601 (2015)
57. Malla, A.M., Sahu, R.K.: Security attacks with an effective solution for dos attacks in VANET. Int. J. Comp. Appl. **66**(22) (2013)
58. Engoulou, R.: Securing vanets using the node reputation method (Doctoral dissertation, École Polytechnique de Montréal).

59. Hasrouny, H., Samhat, A.E., Bassil, C., Laouiti, A.: VANet security challenges and solutions: a survey. Veh. Commun. **1**(7), 7–20 (2017)
60. ETSI T. 102 893 V1. 1.1-ITS-Security-Threat. Vulnerability and Risk Analysis (2010)
61. Singelee, D., Preneel, B.: Location verification using secure distance bounding protocols. In: IEEE International Conference on Mobile Adhoc and Sensor Systems Conference, pp. 7-pp. IEEE (2005)
62. Isaac, J.T., Zeadally, S., Camara, J.S.: Security attacks and solutions for vehicular Adhoc networks. IET Commun. **4**(7), 894–903 (2010)
63. Langley, C., Lucas, R., Fu, H.: Key management in vehicular Adhoc networks. In: 2008 IEEE International Conference on Electro/Information Technology, pp. 223–226. IEEE (2008)
64. AlMarshoud, M., Sabir Kiraz, M., Al-Bayatti H.A.: Security, privacy, and decentralized trust management in VANETs: a review of current research and future directions. ACM Comput. Surv. **56**(10), 1–39 (2024)
65. Wang, Y., Song, J., Zhang, Y.A., Cao, Y.: Decentralized trust management system for VANETs. In: Automated and electric vehicle: design, informatics and sustainability, pp. 241–255. Springer Nature Singapore, Singapore (2022)
66. Xie, L., Ding, Y., Yang, H., Wang, X.: Blockchain-based secure and trustworthy Internet of Things in SDN-enabled 5G-VANETs. IEEE Access. **29**(7), 56656–56666 (2019)
67. Sumit, Chhillar, R.S., Dalal, S., Dalal, S., Lilhore, U.K., Samiya, S.: A dynamic and optimized routing approach for VANET communication in smart cities to secure intelligent transportation systems via a chaotic multi-verse optimization algorithm. Cluster Comput. **15**, 1–26 (2024)
68. Gupta, N., Manaswini, R., Saikrishna, B., Silva, F., Teles, A.: Authentication-based secure data dissemination protocol and framework for 5G-enabled VANET. Future Internet. **12**(4), 63 (2020)
69. Krishnan, P.R., Kumar, P.A.R.: Security and privacy in VANET: concepts, solutions and challenges. In: 2020 International Conference on Inventive Computation Technologies (ICICT), pp. 789–794. IEEE (2020)
70. Hegde, N., Kamble, S.J., Aryalekshmi, B.N., Janardhana, D.R., Ravishankar, H.: Enhancing privacy in VANET cloud: a blockchain-powered identity authentication framework. SN Comp. Sci. **5**(8), 1016 (2024)
71. Khraisat, A., Alazab, A.: A critical review of intrusion detection systems in the internet of things: techniques, deployment strategy, validation strategy, attacks, public datasets and challenges. Cybersecurity. **4**, 1–27 (2021)
72. Amaouche, S., Benkirane, S., Guezzaz, A., Azrour, M.: A proposed machine learning model for intrusion detection in VANET. In: The International Conference on Artificial Intelligence and Smart Environment, pp. 103–108. Springer International Publishing, Cham (2022)
73. Rajapaksha, S., Kalutarage, H., Al-Kadri, M.O., Petrovski, A., Madzudzo, G., Cheah, M.: Ai-based intrusion detection systems for in-vehicle networks: a survey. ACM Comput. Surv. **55**(11), 1–40 (2023)
74. Ding, Q., Li, X., Jiang, M., Zhou, X.: Reputation-based trust model in vehicular Adhoc networks. In: 2010 International Conference on Wireless Communications & Signal Processing (WCSP), pp. 1–6. IEEE (2010)
75. Alanazi, F.: The future of transportation: blockchain-powered solutions. Transp. J. **64**(1), e12032 (2025)
76. Rehman, A., Hassan, M.F., Hooi, Y.K., Qureshi, M.A., Shukla, S., Susanto, E., Rubab, S., Abdel-Aty, A.H.: CTMF: context-aware trust management framework for internet of vehicles. IEEE Access. **7**(10), 73685–73701 (2022)
77. Batool, H., Anjum, A., Khan, A., Izzo, S., Mazzocca, C., Jeon, G.: A secure and privacy-preserved infrastructure for VANETs based on federated learning with local differential privacy. Inf. Sci. **1**(652), 119717 (2024)
78. Navdeti, C.P., Banerjee, I., Giri, C.: Privacy preservation and secure data sharing scheme in fog based vehicular Adhoc network. J. Inf. Secur. Appl. **1**(63), 103014 (2021)
79. Cao, Y., Xu, S., Chen, X., He, Y., Jiang, S.: A forward-secure and efficient authentication protocol through lattice-based group signature in VANETs scenarios. Comput. Netw. **4**(214), 109149 (2022)

80. Upadhyay, P., Marriboina, V., Goyal, S.J., Kumar, S., El-Kenawy, E.S., Ibrahim, A., Alhussan, A.A., Khafaga, D.S.: An improved deep reinforcement learning routing technique for collision-free VANET. Sci. Rep. **13**(1), 21796 (2023)
81. Muktar, B., Fono, V., Zongo, M.: Predictive modeling of signal degradation in urban VANETs using artificial neural networks. Electronics **12**(18), 3928 (2023)
82. Lyamin, N., Kleyko, D., Delooz, Q., Vinel, A.: AI-based malicious network traffic detection in VANETs. IEEE Network **32**(6), 15–21 (2018)
83. Liu, B., Xu, G., Xu, G., Wang, C., Zuo, P.: Deep reinforcement learning-based intelligent security forwarding strategy for VANET. Sensors. **23**(3), 1204 (2023)

Securing VANETs for Internet of Things (IoT): AI-Driven Solutions for Privacy and Intrusion Detection

Tayyaba Basri

Abstract In IoT-enabled smart cities vehicular ad hoc networks (VANETs) are necessary for smart transport systems, yet combining them with 5G and high mobility settings presents significant safety concerns. The flexibility, immediate attack reaction, and new malicious attacks like Sybil, GPS spoofing, and AI-driven attacks that compromise accuracy of data, privacy and system reliability are challenges for traditional centralized security frameworks. As a way to tackle these challenges this research presents a unique AI-blockchain hybrid system which combines blockchain technology for decentralized trust management with machine learning (ML) for reactive identification of intrusions. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) are two Deep Learning models which our approach uses for identifying evolving risks like DDoS and Man-in-the-Middle attacks with 96% accuracy. Additionally, blockchain guarantees unbreakable verification of identities and data origins which decreases Sybil attacks by 40%. Additionally, by overcoming delays and scalability problems that classical Public Key Infrastructure (PKI) has, Elliptic Curve Cryptography (ECC) strengthens confidentiality verification. By applying comprehensive investigation this study demonstrate how the combined system helps immediate action in changing VANET networks while also reducing growing security threats. The proposed model provides a strong basis for future smart cities where effectiveness and safety are crucial by promoting the development of safe, adjustable, and privacy aware modes of transport.

Keywords VANET · IoT · IDS · AI · ML

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1 Introduction

This paper focuses on Vehicular Ad Hoc Networks (VANETs), which were invented due to the development of vehicle technology, intelligent transportation systems, and wireless communication. Improves the effectiveness of the system through direct communication among automobiles and other mobile devices, not relying on roadside units [1]. The Internet of Things (IoT) has brought about changes to both industries and to people's lives by linking devices such as appliances in homes and factories and controlling and communicating with them intelligently. This connectivity has enhanced efficiency but has opened up new security risks since many IoT devices are resource constrained and hence easily compromised by attackers [2]. There are great potentials of enhancing VANETs with the increasing application of artificial intelligence (AI) techniques in various areas such as data processing, healthcare, and cyber security. Methods like Swarm Intelligence (SI) and Machine Learning (ML) have a lot of promise for resolving the issues VANETs faces. Although AI is being integrated in VANET systems, not enough research has been done to determine how these techniques may be completely utilized to enhance interactions between vehicles [3]. Based on their goals and the attacker's level of system knowledge, adversarial attacks can be classified. Having said that, there are four primary categories. Non-targeted attacks use minor adjustments, such as random noise, to trick machine learning models into generating inaccurate or unwanted results without concentrating on a particular label or class. By carefully changing inputs to resemble the intended target, targeted attacks, on the other hand, are more active and seek to cause models create particular wrong outputs. Because they produce a single mutation or pattern that deceives the model across a broad range of inputs, unrelated of the particular data, universal attacks are more potent and difficult [4].

The fast and decentralized mobility of cars is making it difficult for conventional safety techniques in Vehicular Ad-Hoc Networks (VANETs), for example fixed cryptography and centralized Public Key Infrastructure (PKI), to remain ahead. By itself centralized architectures mostly rely upon a single entity to govern trust. This leaves them vulnerable to accidents or attacks like as Sybil attacks, which use developed credentials to bombard networks with false data, or DDoS occurrences, in which excessive traffic can paralyze the system [5]. PKI systems slow certificate revocation process raises these dangers. Delays in upgrading certificates for example, may lead to problems for attackers to take advantage of when vehicle identities get hacked especially in conditions where cars travel quickly between zones [6]. Due to their dependency on databases of known attacks, current intrusion detection techniques are very limited which leaves networks vulnerable to new attacks like as adversarial AI attacks that secretly change sensor data to mislead car systems [4]. Such weaknesses highlight the need for flexible, autonomous security methods that protect personal information against new intruders must be developed.

A significant approach can be obtained by combining blockchain technology with machine learning. By ensuring that vehicle identifies are verified by peer consensus instead of a central authority, blockchain's distributed ledger architecture successfully prevents Sybil attacks. By implementing multi-node validation for data broadcasts, the latest research showed that blockchain based trust frameworks decrease the flow of harmful messages by 40% in simulated traffic conditions [7]. In the meantime, current anomaly detection is an advantage of machine learning algorithms. Data shows that by learning conventional traffic behavior and identifying mistakes support vector machines (SVMs) can detect 98.7% of flooding attacks and grayhole attacks in which nodes actively eliminate data [8]. Security is further enhanced by technologies like software defined networking (SDN) used in combination with decentralized intrusion detection systems. These methods use blockchain technology to safely distribute attack reports throughout the network and generating a verifiable, unbreakable record and deep learning to spot previously unknown vulnerabilities [9]. In comparison with older PKI models the tasks like the ABAKA protocol decrease authentication latency by 35% by combining ML based behavior modeling with lightweight authentication solutions (such elliptic curve cryptography) [10]. Figure 1 shows the architecture of VANET.

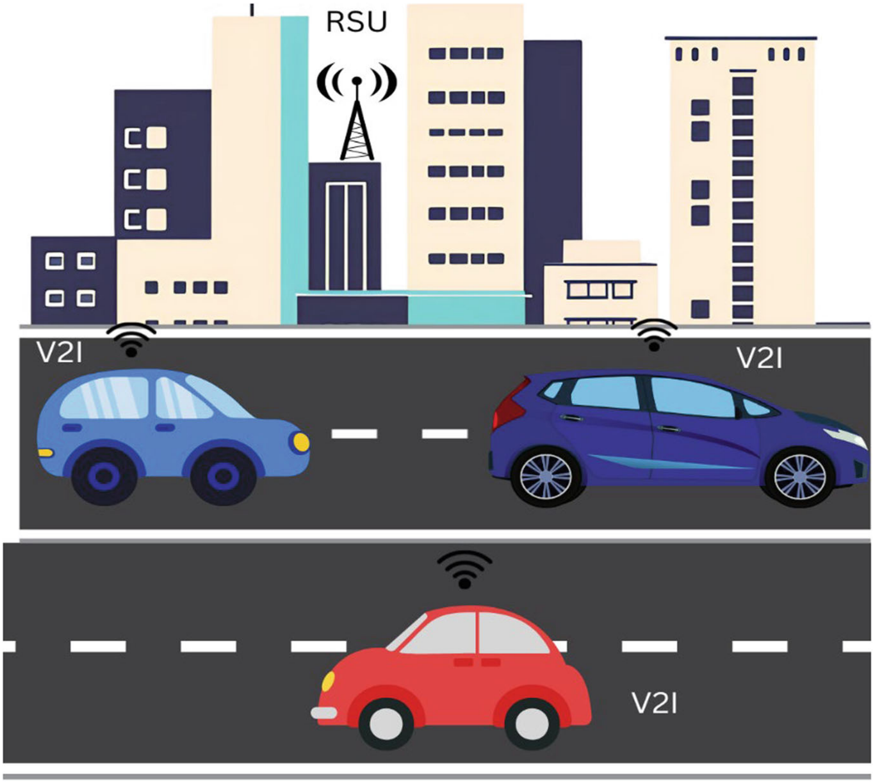

Fig. 1 Architecture of VANET

2 Literature Review

VANETs now support various services beyond safety applications, thanks to advances in car hardware and software, including infotainment, driver assistance, and video-on-demand services. Although these advancements enhance user experience and transit efficiency, they also present security, privacy, performance, and Quality of Service (QoS) issues [11]. Vehicle-to-Everything (V2X) research makes extensive use of AI techniques like swarm intelligence and deep learning, which enhance safety and communication in transportation systems. Predicting traffic flow, increasing optimization algorithms, simplifying signal timing design, using machine learning to control congestion, striking a balance between performance and fairness, guaranteeing user acceptance, improving privacy, and integrating communication systems like DSRC and C-V2X are some of the areas that still face challenges. Building confidence in AI-powered vehicle safety, preventing unforeseen issues from AI solutions, testing user reactions to AI in V2X, protecting privacy while monitoring fleets of vehicles, enhancing the detection of anomalies and attacks in V2X networks, utilizing Mobile Edge Computing (MEC) for real-time safety in autonomous driving, and addressing the cost and implementation of DSRC are some of the unresolved issues [12]. Another way to group AI systems is by their level of understandability; interpretable AI differs from non-interpretable AI. Neural networks (NN) and other algorithms are frequently referred to as "black-box systems" since they excel at predicting recommendations but have difficulty explaining how they do so. Such systems are challenging to examine and verify due to their lack of transparency [13].

There are still security problems in VANETs especially when it comes to protecting user privacy. Using pseudonym linkage techniques to monitor vehicles is an ongoing challenge particularly in very unstable network conditions [14]. Due to delayed certificate validations, centralized public key infrastructure (PKI) models which are frequently employed for authentication face operational challenges in high speed scenarios. Attacks via Sybil or imitation by attackers are more likely as a result of these inefficiencies [15]. Due to their failure to adjust quickly to sudden topology changes or network spikes, legacy intrusion detection systems (IDS) that rely on preset algorithms find it difficult to fight advanced attacks like machine learning augmented DDoS operations. Responsive machine learning and blockchain decentralized trust mechanisms have been combined in emerging hybrid techniques. Blockchain tamper proof ledgers, for example, have been shown in experimental experiments to lower pseudonym abuse rates by over one-third, strengthening control without sacrificing privacy [16]. Meanwhile, deep learning algorithms, such as CNNs beat antiquated signature matching methods by achieving 97% accuracy in identifying novel incursions by mapping minor shifts in data flow.

References	Advantages	Limitation
[17]	Vehicle-to-everything (V2X) communication is essential because it allows cars to talk to other cars, infrastructure, and other objects like pedestrians, allowing for smart driving	V2X communication faces serious security threats that must be addressed effectively
[18]	ML models, including Random Forest (RF), Extra Trees (ET), XGBoost, and LightGBM, using the processed CICIDS dataset to find the best model for building an Intrusion Detection System (IDS)	The research's modest sample size and diverse datasets may restrict the ability to generalize of its findings. Additionally, it depends heavily on high-quality data, which isn't always accessible in real-world scenarios
[19]	The Internet of Vehicles (IoV), which combines AI and machine learning, has transformed the development of smart cars. It enables automobiles to communicate with their surroundings and connect to public networks	However, there are still issues with data processing, cloud network integration, big data management, and effective vehicle-to-vehicle communication
[20]	Vehicle-to-Everything (V2X) enables information exchange between vehicles and their environment. This significant development goes beyond simple communication and improves the safety and sustainability of urban areas by enabling vehicles to speak with traffic signals and road signs	However, it might be difficult to integrate V2X with current infrastructure, and in order to ensure compatibility, changes or modifications are frequently needed. Due to the need to set up vehicle sensors and secure communication channels, V2X network deployment is highly costly

3 The Role of IoT in Enhancing Vanet Communication

The Internet of Things (IoT) connects different devices to the Internet so that they can share data and communicate without human assistance. Social networks (SNs) and this approach work together to create a network infrastructure that permits communication between autonomous devices. Accordingly, by creating social networks among devices based on shared services and interests, the Social Internet of Things (SIoT) improves user experiences. SIoT can be crucial in Vehicular Ad Hoc Networks (VANETs) to enable effective communication between humans and IoT-enabled smart cars [21]. Applications of IoT have also expanded to smart cities, where governments use the technology for urban planning, infrastructure preservation, and environmental monitoring. The Internet of Things (IoT) has improved everyday life, business operations, and urban development by enabling seamless communication and connecting intelligent gadgets, thereby changing how we interact with the outside environment [22].

Significant data security and privacy issues are raised by the widespread use of 5G-enabled IoT due to its easier connectivity and integration of satellite and terrestrial

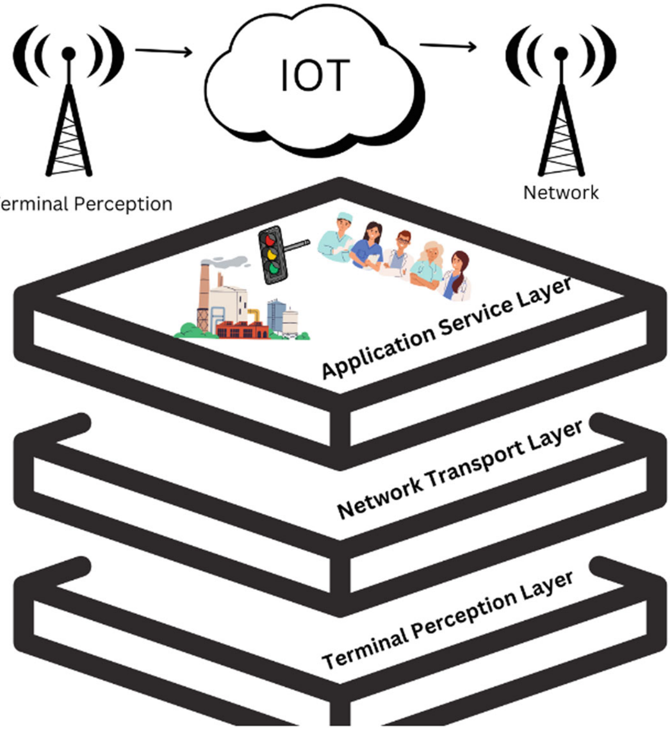
IOT
Terminal Perception
Network
Application Service Layer
Network Transport Layer
Terminal Perception Layer

Fig. 2 Three-tier architecture of IoT

networksBut it additionally provides a lot of opportunities to gather digital evidence, which is essential for checking into security events and cybercrimes. This evidence must be properly gathered, safely maintained, and thoroughly examined in order for 5G IoT networks to be implemented successfully [23]. The IoT's three-tier design is shown in Fig. 2.

3.1 Key Challenges in Vanet-Enabled IoT Environments

The spreading of invalid data is a major issue in Vehicle Ad Hoc Networks (VANETs) which can harm safety and stop navigation. A Misbehaviour Detection System (MDS) identifies fake data that is sent within the system instead of actually applying misconduct units [24]. Routing in VANETs is hard due to the heavy traffic and always shifting connections and repeated failures of networks. Both outside problems like the road design and blockages that block signals and inside factors such as vehicle speed and unstable motion can have an effect on routing systems.

For addressing these unexpected situations transport system have to be very flexible. This means choosing on ideal sending and routing methods and using the right model for transmitting signal and motion of vehicle [25]. The network structure of VANETs is highly open to attackers growing issues on possible stability. Since actual VANET deployment is difficult and costly simulation are usually used as a cheaper and easier choice. These simulations' accuracy might not, however, always correspond to actual situations. Studies have indicated that the selection of mobility models in simulations significantly influences the realism of the outcomes [26].

Unauthorized access to private vehicle data is an aspect of VANET privacy threats. A car and its driver are directly connected; thus, any violation of this data compromises the privacy of the driver. Since the owner of the car is typically also the driver, both the owner's and the vehicles privacy are at risk if an attacker manages to obtain the owner's identification. Identity disclosure is the term for this kind of attack. Location monitoring, in which a hacker tracks the position or path taken by the vehicle, is another common privacy risk. This data is regarded as private and may be exploited [14]. Although cloud data centers are utilized on the back end of VANETs, there are certain difficulties because of their centralization. Large data transfers, such CCTV footage or traffic and road sensor data, are difficult for centralized cloud computing to manage because of unnecessary latency. For example, drivers must make fast decisions to change lanes, avoid traffic, or find parking spaces in a busy city. These situations need for quick reactions, which centralized cloud solutions aren't always able to deliver [27].

3.2 Common Attacks Targeting Vanet Security

VANET is an automated network created between vehicles having communication capabilities. Although the design and implementation of VANETs have advanced significantly, their security issues have received far less attention. VANETs, a crucial part of Intelligent Transportation Systems (ITS), have enormous potential to improve traffic safety and make a variety of value-added services possible.

VANET security is still a major concern, though. Recently, a variety of attacks have surfaced that jeopardize these networks' availability, privacy, and integrity. For VANET applications to be dependable and trustworthy, secure communication is necessary [28].

A. Denial of Service Attack (DOS)

One of the biggest risks to any network is a Denial of Service (DoS) attack. A denial-of-service attack's main objective is to prevent legitimate users from using network services. Attackers do this by flooding the network with false messages, which causes congestion. This causes the network to become overloaded, diverting focus or decreasing the network's overall effectiveness.

B. Distributed Denial of Service (DDoS)

In a VANET setting, a Distributed Denial of Service (DDoS) attack presents a far greater danger than a DoS attack. This is due to the distributed nature of DDoS attacks. In this kind of attack, a real vehicle is simultaneously targeted by several threatening cars from various locations. Additionally, they could transmit their fake communications at various times, which makes it extremely difficult to identify, stop, or track down the attack.

C. Black Hole Attack

In a network, a "Black Hole Attack" occurs when hostile nodes trick other nodes into sending data via them. These malicious nodes share fake routing information to make it appear as though they had the best path to the target. The malicious nodes disrupt the network by either dropping the data or misusing it for their own gain once the sender has trusted them and sent the data.

D. Wormhole Attack

A Wormhole Attack is a kind of Black Hole Attack in which malicious vehicles create a fake shortcut or tunnel between the sender and the recipient, making it appear as the shortest path in the network's routing table. When looking for the simplest way to transfer data the sender choose this fraud route. Once transmission starts over this false the tunnel its safety fails because hackers may interrupt the data and listen on them corrupt them or misuse it for themselves.

E. Illusion Attack

An illusion attack happens when a hacker precisely sends incorrect details to Road Side Units (RSUs) and close car about congestion or his or her vehicle. Because driver use such signal to drive safely these fraud messages have the capacity to misleading them affecting their ability to drive and might result in accidents or connectivity problems.

F. Timing Attack

In VANET a time attack occur when a suspicious car purposely slows essential signals. Because cars rely on real time data delays may make it ineffective. When a hacker delayed sending a crucial message it arrives at the receiver too late which lead to this attack. This delay might occur to accidents and wrong choices or poor connectivity.

G. Man in Middle Attack

When an attacker vehicle silently detects the communications of two cars in a VANET this is known as a man in middle attack. It controls the conversation while deceiving both cars into believing they are speaking to one another directly. This gives a hacker a way to changed transmissions and adds false material or take information while pretending that an everyday talk is happening.

H. Global Positioning System (GPS) Spoofing

When a hacker transmits fake location signals to mislead the GPS system, this is known as GPS spoofing in VANET. In this technique, the hacker's vehicle employs a GPS simulator to send stronger fake signals than the real ones. GPS tracks automobiles using signals and unique IDs. This makes other vehicles assume they are at the wrong area, leading to confusion, accidents, or network difficulties.

I. Social Attack

A social attack occurs when an attacker attempts to indirectly create problems by affecting network users' behavior. "You are stupid" and other random, insulting, or discouraging remarks are sent to legitimate users by the attacker. Users' behavior may shift from positive to negative after reading these messages, becoming irritated or upset, which may cause disruptions to the network or their behavior.

J. Sybil Attack

A sybil attack is a risky attack in which the attacker creates several fake identities or vehicles within the network. By creating the appearance of a large number of vehicles, the attacker can gain control of the network or spread misleading information. This may hinder the performance of the network harming authorized users. This attack is extremely challenging to identify and stop because the attacker may even pretend to be in multiple places at once [29].

4 Artificial Intelligence for Strengthening Vanet Security

Intelligent Transportation Systems (ITS) are a crucial part of the Internet of Things in the context of smart cities. Even though ITS has many of the same general features as IoT, it also has unique needs, like precise timing, dynamic environments, and the ability to handle massive amounts of data. Strong cyber security is one of the most important requirements of ITS. Applications of ITS are often divided into three categories: entertainment, road traffic efficiency, and transportation safety. To guarantee the physical safety of road users, road safety applications must meet strict real-time standards and have strong cyber security safeguards. Applications for distraction and road traffic efficiency need high levels of cyber security even though they are not directly related to safety. Any compromise in these systems may affect ITS's overall functionality [30].

Commonly found in automobiles, the CAN (Controller Area Network) bus protocol is developed to guarantee reliable communication and safety during operation. It was not, however, constructed with robust safeguards against current cyber security threats. The quantity of Electronic Control Units (ECUs) in automobiles is also growing quickly. Because every ECU adds possible weaknesses to the system, this growth increases the probability of cyber-attacks. Since low latency is necessary to guarantee the dependability and availability of safety–critical functions, latency is one of the most important components of CAN bus security. Denial-of-Service (DoS) attacks, in which difficult traffic results in bandwidth congestion and delays vital connections, can unfortunately take advantage of latency. The vehicle's systems might fail to function as planned as a result of such delays [31].

Researchers are trying to find ways to protect autonomous cars and their networks against malware and cyber-attacks that take advantage of Connected Vehicles (CVs) as they exchange data. This entails determining the origin of the attacks and examining the CVs to determine the mode of infection transmission. Predicting possible threats to autonomous vehicle networks (AVN) and data communication between autonomous cars (DCAV) is crucial for the efficient detection of these attacks. The complexity is increased by the fact that more recent CV types have extremely brief communication cycles, making it difficult to identify and stop attacks [32].

5 Advanced AI Strategies for Security Vanets

References	Advantages	Limitations
[33]	IoT security is improved by machine learning (ML) algorithms, such as transaction and decision algorithms, which preprocess data and make effective decisions	Limited to predefined models and could need a lot of training data to function well in changing and dynamic settings
[34]	Advanced defense against cyberattacks using AI and ML methodologies is offered by AI-based solutions such as Darktrace, Deep Armor, and Cognigo's Data Sense	Because AI technologies cannot completely replace human intelligence, more effective solutions require a "human-in-the-loop" strategy
[35]	Massive traffic data may be efficiently analyzed by AI and ML to spot patterns and prevent attacks	The financial effect of cyberattacks is expected to increase from $3 trillion to $5 trillion by 2024, indicating that their size may surpass present AI capabilities
[36]	Microsoft and Pacific Northwest National Laboratory's neural networks and GANs effectively provide malicious inputs to find vulnerabilities	Needs a lot of processing power and might still have trouble finding new attack techniques or cautiously hidden vulnerabilities

5.1 Predictive Security in Vanets: Machine Learningmodels

IoT devices, like sensors, generate massive amounts of data at an increasing rate; for instance, data size was projected to grow from 44 zettabytes in 2020 to 163 zettabytes by 2025. Traditional servers are unable to handle this data, which gives attackers the opportunity to exploit vulnerabilities using techniques like ransom ware or SQL injections.

A. Machine Learning as a Solution

Machine Learning (ML) provides an effective solution by processing large datasets, identifying anomalies, and updating models in real-time. Organizations invest heavily in ML to secure their systems because these models can detect abnormal patterns more quickly and accurately [37]. An anomaly detection system that uses the Principal Component Analysis (PCA)-subspace approach in network backbones was subjected to three poisoning attacks by Rubinstein et al. They demonstrated how even a tiny quantity of incorrect information might drastically impair the detector's functionality. Although this method is simple and efficient, it is only applicable to binary classification and is not applicable to other learning techniques.

B. Chronic Poisoning Attacks on Machine Learning

The Edge Pattern Detection (EPD) technique was used by Li et al. to create a chronic poisoning attack against machine learning-based intrusion detection systems (IDS). Support Vector Machines (SVM), Logistic Regression (LR), and Naive Bayes (NB) are just a few of the learning algorithms that can be targeted by this method. However, this approach is difficult to use and depends on a steady, long-term poisoning process [38]. Both sides of the cybersecurity battle use machine learning techniques: attackers use them to take advantage of vulnerabilities, and defenders use them to identify threats.

C. Evaluation of Machine Learning Models for Threat Detection

Using widely used benchmark datasets, this review evaluates how well three learning models detect and categorize malware, spam, and intrusions. The evaluation was built on metrics such as recall, accuracy, and precision [39].

6 Vanet Privacy and Intrusion Detection Solutions

Because high-density communication networks contain many interrelated parts, they require quick and precise Intrusion Detection Systems (IDS) to remain safe. Threats such as insider threats, denial-of-service (DoS) attacks, scanning attempts, illegal access, and novel (zero-day) attacks may all be detected by IDS. IDS secure sensitive information and overall stability by using AI to find unusual activities and identify patterns by letting users to react quickly to threats [40].

As information numbers grow ML help in spotting unusual features in VANET. A number of ML algorithms like Support Vector Machines (SVM) and neural networks, decision trees and also Bayesian methods use by IDS for VANET. The Bayesian strategy which relies on Bayes theorem makes a guarantee that each element of a situation in VANET performs freely. The Naive Bayes classifier operates perfectly with complicated data and has been simple to use and gives ideal performance in classification. It works as well on very massive data sets [8].

The Random Forest algorithm in intrusion detection systems is good at detecting a variety of cyber attacks such as flood and gray hole attacks. It can achieve high accuracy using an array of six key characteristic. It not just secures the system from assaults but also improve the reliability and speed of wireless sensor networks [41]. Explainable Artificial Intelligence (XAI) is beneficial for VANET security because it reduces AI decisions. This allows management and clients figure out the reason behind what decisions AI detectors make that they might react properly. By increasing the openness and understanding of AI driven security XAI increase trust in VANET protections. [16].

Public Key Infrastructure (PKI) is needed for private access to and control in networked controls, cloud networks, and V2V connections. In various network arrangements, it aids in verification of identity and safeguards data against exploitation [42]. Vehicles can link and exchange critical safety data via a Decentralized Mesh Network (DMN), improving road safety and communication. In this network, every vehicle acts as a connector, extending its reach and resilience. Without a central authority, the system keeps in touch and adapts to errors. Security is ensured by end-to-end encryption and trust mechanisms, which verify the authenticity of communications and prevent harmful attacks. The DMN is scalable, reliable, and secure, and it can handle a variety of vehicle numbers at various places [43].

Machine learning ability to identify trends is essential in modern intrusion detection. A significant improvement over rigid rule based frameworks that are insufficient against changing methods of attack is provided by Long Short-Term Memory (LSTM) networks which, for instance, examine time series traffic information to identify DDoS anomalies with 96% reliability [44]. In a similar way grayhole and wormhole intrusion detection is enhanced by 22% using combined methods like Random Forest (RF) which analyze packet routing deficiencies thoroughly [37]. The unchanging audit files of blockchain technology offer forensic integrity to bridge trust issues in shared IDS setups. Distributed ledger backed solutions decrease error rates by 18%, according to Gupta et al. [37] by keeping tamper evident records of attack incidents which accelerates post-incident examinations [32].

Modern systems use machine learning for real-time identification of anomalies in order to defend against Man-in-the-Middle Attacks (MIMAs). Convolutional Neural Networks (CNNs) for example, have shown an amazing amount of effectiveness in identifying spying efforts. CNNs identify attack by analyzing minute shifts such as irregular signal patterns or microseconds of delay in data packets, in opposed to outdated threshold-based techniques. A recent research study suggests that these models achieve an efficiency of 94% in identifying suspicious behaviors by outperforming traditional methods that cannot react to new dangers [32]. Combining the concept of blockchain to this develops another line of defense. Hybrid frameworks which involve decentralized ledgers and machine learning have took over vehicle network protection. Smart contracts lessen MIMA attacks by over a third [34] by concluding session keys during communications. By developing algorithms for detecting right away on vehicle information without centralizing private data decentralized federated learning tackles privacy challenges while maintaining a balance between privacy and the high efficiency requirements of VANETs [38].

7 Cryptographic Solutionfor Privacy in Vanets

Vehicular Ad Hoc Networks (VANETs) provide useful features by enabling data sharing and communication between vehicles. However, these networks have difficulty meeting the high needs of 5G technology as the number of cars increases. By eliminating points of failure and enabling peer-to-peer communication, decentralized systems improve security, privacy, and reliability, making them a promising alternative. Vehicles may safely manage communication and trust by utilizing cutting-edge technologies like digital wallets and contemporary cryptographic techniques. Researchers are investigating decentralized alternatives and becoming ready for future requirements, such as quantum-resistant security, because traditional systems that rely on central authorities have limitations [5]. Elliptic Curve Cryptography (ECC) is a safe technique that protects data and guarantees privacy by utilizing the mathematical features of elliptic curves. Intruders feel it hard to get past the Elliptic Curve Discrete Logarithm challenge (ECDLP) because it is challenging to figure out. VANET use Elliptic Curve Cryptography (ECC) for private way of authentication and safe transmission. These strategies provide secured transmission of data by using pseudonyms and secret keys and hidden identity. Many of these ideas involve boosting the process by avoiding overhead and keeping privacy while maintaining that cars and RSU can verify one another. This facilitates the release of false details and maintains safety in VANETs [6]. Additional services have been rendered possible by Huang et al.'s Anonymous Batch Authentication and Key Agreement (ABAKA) technique, which facilitates secure communication between vehicles and service providers (SPs). By enabling the authentication of numerous cars simultaneously rather than one at a time, ABAKA enhances the procedure. Private keys and pseudonyms are used to provide cars with privacy while maintaining security, and Tamper-Proof Devices (TPDs) are used to create keys using ECC [15].

Elliptic Curve Cryptography (ECC) is getting more common in VANET security due to takes smaller keys and is free to quantum attacks. Fast identification is made feasible without risking car ID. This is crucial when you face a danger to security and action occur rapidly [6].

Also regular surveillance becomes easier by combining blockchain technology with machine learning resulting in easier to detect attacks and sustain safety. Think about smart contracts that apply embedded machine learning algorithms to detect unauthorized activity in addition to performing operations. It greatly raises the rates of which attacks are detected by system [45]. Progress are being improved by blockchain technologies like as zero knowledge proofs that give automobiles the ability to check who they are without giving information and Merkle trees that tie actions to open data and offer an irreversible inspection path. Together these tools are changing VANETs validity and trustworthiness [46].

7.1 Blockchain-Based Privacy for Vanets

High node mobility and instability and security are some of the problems that VANETs deal with. The spread of false data, such as phony emergency alerts provided by attackers, poses an important risk to the effectiveness and security of transportation. To address these issues, a blockchain-based method for authentication and trust management is proposed. The trust management approach evaluates the vehicle's and the data's dependability in order to detect and prevent false information [45]. When a leaf node is added or removed in response to a certificate being issued or revoked by the Certificate Authority (CA), the Merkle Patricia Tree (MPT) updates its root. These changes and transactions are documented periodically in a Certificate Management Tree (CMT).

The blockchain stores the MPT (Certificate Root) and CMT (Transaction Root) roots in an immutable manner [7]. A blockchain-based anonymous reputation system that uses reputation certificates was proposed by Lu et al. [46] to stop cars from broadcasting false messages. Similar to this, Yang et al. made use of blockchain technology, which records a car's reputation directly on blocks. These blocks are made and maintained up by the cars that are adjacent to the one being evaluated. A distributed public ledger protected by hash functions, proof-of-work (PoW) consensus, and Merkle trees, blockchain was first introduced with the Bitcoin protocol in 2008. Blockchain is appropriate for developing trust models in VANETs because of these characteristics. Any network entity can verify the permanent and tamper-proof ledger that it creates by recording all messages and authority acts. However, since transactions associated with a public key can be linked to actual identities by looking at the ledger, privacy was not considered in the original design of Bitcoin [47].

8 Intrusion Detection Systems (IDS) in VANETs

There are two types of attacks in VANETs: internal and external. Digital signatures along with other cryptographic techniques are used to prevent internal attacks, but they are unable to identify external ones. An Intrusion Detection System (IDS) is required to manage external threats like Brute Force, Botnet, Ports can, and Denial of Service (DoS) attacks [44].

A. Intrusion Detection System (IDS) Deployment

The performance of IDS varies depending on where it is deployed; it typically goes on cars, cluster heads, or roadside units (RSUs). The majority of intrusion detection systems, however, are restricted to identifying anomalous activity brought on by particular kinds of attacks within their local sub-network and focuses on particular areas of the VANET. This makes it impossible to monitor the VANET as a whole. As a result, creating an improved intrusion detection system (IDS) that can identify any unusual network activity throughout the VANET system is essential [9]. Any

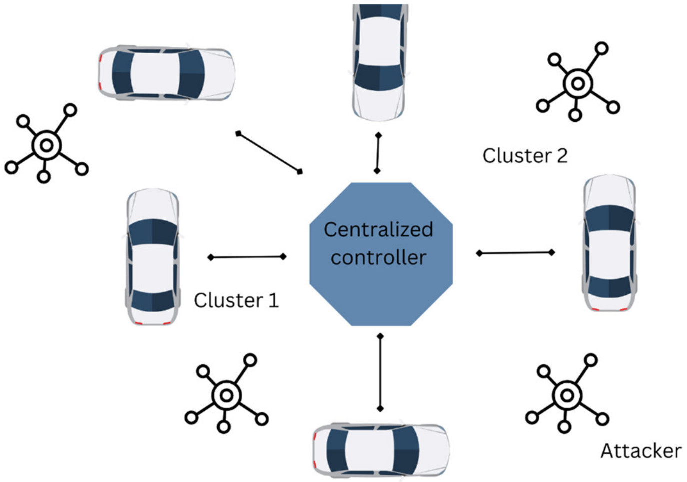

Fig. 3 VANET systems, which connect multiple vehicles to the centralized controller

activity that compromises the availability, confidentiality, or integrity of resources is referred to as intrusion in VANET. Firewalls and intrusion prevention systems make up the first line of defense, while intrusion detection systems (IDS) make up the second. Intruder and intrusion types, detection techniques, data sources, core location, infrastructure, and usage frequency are some of the variables that can be used to classify intrusion detection systems (IDS) [48].

B. Machine Learning Approaches in IDS for VANET

IDSs in VANET detect cyber attacks using a variety of machine learning (ML) approaches. To categorize opposed nodes, these systems examine features taken from wireless network traffic. The location of the IDS deployment and high-quality training datasets are two essential components for reliable detection. While collaborative IDSs may encounter difficulties such as slower detection times and performance problems when vehicles exit the network, lightweight distributed IDSs are made to minimize computing complexity [49]. Figure 3 shows the VANET systems, which connect multiple vehicles to the centralized controller, which is called RSU module. The attackers mostly affected the interference between each vehicle and the interference between the vehicle and the centralized controller.

9 Conclusion

Vehicular ad hoc networks or VANET are an innovation in intelligent transportation systems that integrate with the Internet of Things (IoT) ecosystem. But the fast interaction changes set forth by 5G and AI driven systems come with major safety and detection problems. In addition to cryptographic solutions like Elliptic Curve Cryptography (ECC) and blockchain for protected interaction and identity security this work highlight the importance of AI like ML and DL as they enhance VANET capacity to identify and prevent challenges. Despite the encouraging advancements, VANET have difficulties including increased mobility and the requirement for real-time reaction which necessitate reliable and expandable security solutions. Despite AI outstanding danger prediction and intrusion detection skills, its need on high quality data and computing power continue to be a drawback. Like to this blockchain and encryption technologies increase safety and security, but they also present challenge for scalability and interoperability with existing systems.

Future research should concentrate on improving system scalability by adjusting to changing cyber threats and closing the separation between concepts and real world operations in order to guarantee the security and effectiveness of VANETs in IoT enabled smart cities. For next-generation transport networks, VANETs may provide a safe and private environment by combining state-of-the-art cryptographic frameworks with AI-driven innovations.

References

1. Mchergui, A., Moulahi, T., Zeadally, S.: Survey on artificial intelligence (AI) techniques for vehicular ad-hoc networks (VANETs). Veh. Commun. **34**, 100403 (2022)
2. Abreu, R., Simão, E., Serôdio, C., Branco, F., Valente, A.: Enhancing IoT security in vehicles: a comprehensive review of AI-driven solutions for cyber-threat detection. AI **5**(4), 2279–2299 (2024)
3. Saoud, B., Shayea, I., Yahya, A.E., Shamsan, Z.A., Alhammadi, A., Alawad, M.A., Alkhrijah, Y.: Artificial Intelligence, Internet of things and 6G methodologies in the context of vehicular Ad-hoc networks (VANETs): survey. ICT Express (2024)
4. Aouedi, O., Vu, T.H., Sacco, A., Nguyen, D.C., Piamrat, K., Marchetto, G., Pham, Q.V.: A survey on intelligent Internet of Things: applications, security, privacy, and future directions. IEEE Commun. Surv. Tutor. (2024)
5. AlMarshoud, M., Sabir Kiraz, M., Al-Bayatti, H.A.: Security, privacy, and decentralized trust management in VANETs: a review of current research and future directions. ACM Comput. Surv. **56**(10), 1–39 (2024)
6. Al-Shareeda, M.A., Anbar, M., Manickam, S., Khalil, A., Hasbullah, I.H.: Security and privacy schemes in vehicular ad-hoc network with identity-based cryptography approach: a survey. IEEE Access **9**, 121522–121531 (2021)
7. Lu, Z., Wang, Q., Qu, G., Zhang, H., Liu, Z.: A blockchain-based privacy-preserving authentication scheme for VANETs. IEEE Trans. Very Large Scale Integr. (VLSI) Syst. **27**(12), 2792–2801 (2019)
8. Alsarhan, A., Alauthman, M., Alshdaifat, E.A., Al-Ghuwairi, A.R., Al-Dubai, A.: Machine Learning-driven optimization for SVM-based intrusion detection system in vehicular ad hoc networks. J. Ambient. Intell. Humaniz. Comput. **14**(5), 6113–6122 (2023)
9. Shu, J., Zhou, L., Zhang, W., Du, X., Guizani, M.: Collaborative intrusion detection for VANETs: a deep learning-based distributed SDN approach. IEEE Trans. Intell. Transp. Syst. **22**(7), 4519–4530 (2020)
10. Maria, A., Pandi, V., Lazarus, J.D., Karuppiah, M., Christo, M.S.: BBAAS: blockchain-based anonymous authentication scheme for providing secure communication in VANETs. Secur. Commun. Netw. **2021**(1), 6679882 (2021)

11. Haddaji, A., Ayed, S., Fourati, L.C.: Artificial Intelligence techniques to mitigate cyber-attacks within vehicular networks: survey. Comput. Electr. Eng. **104**, 108460 (2022)
12. Mohiuddin, M.A., Nirosha, K., Anusha, D., Nazeer, M., NV, G.R., Lakhanpal, S.: AI to V2X privacy and security issues in autonomous vehicles: survey. MATEC Web Conf. **392**, 01097. EDP Sciences (2024)
13. Oluwafemi, N.: AI-driven adaptive access control mechanisms for autonomous vehicle systems: IoT sensor. J. Artif. Intell. Res. Appl. **3**(1) (2023)
14. Ahmed, N., Deng, Z., Memon, I., Hassan, F., Mohammadani, K.H., Iqbal, R.: [Retracted] A survey on location privacy attacks and prevention deployed with IoT in vehicular networks. Wirel. Commun. Mob. Comput. **2022**(1), 6503299 (2022)
15. Manivannan, D., Moni, S.S., Zeadally, S.: Secure authentication and privacy-preserving techniques in Vehicular Ad-hoc NETworks (VANETs). Veh. Commun. **25**, 100247 (2020)
16. Saleem, M., Farooq, M.S., Shahzad, T., Hassan, A., Abbas, S., Ali, T., Aggoune, E.H.M., Khan, M.A.: Secure and transparent mobility in smart cities: revolutionizing AVNs to predict traffic congestion using MapReduce, private blockchain and XAI. IEEE Access (2024)
17. Grabowska, A.: Adaptive intrusion response systems for autonomous vehicle networks. J. AI Healthc. Med. **3**(2), 1–20 (2023)
18. El-Gayar, M.M., Alrslani, F.A., El-Sappagh, S.: Smart collaborative intrusion detection system for securing vehicular networks using ensemble machine learning model. Information **15**(10), 583 (2024)
19. Alkarim, A.S., Al-Ghamdi, A.S.A.M., Ragab, M.A.H.M.O.U.D.: The Internet of Vehicles (Iov) technology: challenges and solutions. J. Theor. Appl. Inf. Technol. **101**, 7629–7639 (2023)
20. Rishiwal, V., Agarwal, U., Alotaibi, A., Tanwar, S., Yadav, P., Yadav, M.: Exploring secure V2X communication networks for human-centric security and privacy in Smart cities. IEEE Access (2024)
21. Mahi, M.J.N., Chaki, S., Ahmed, S., Biswas, M., Kaiser, M.S., Islam, M.S., Sookhak, M., Barros, A., Whaiduzzaman, M.: A review on VANET research: perspective of recent emerging technologies. IEEE Access **10**, 65760–65783 (2022)
22. Qafzezi, E., Bylykbashi, K., Higashi, S., Ampririt, P., Matsuo, K., Barolli, L.: A fuzzy-based approach for the assessment of the edge layer processing capability in SDN-VANETs: a comparative study of testbed and simulation system results. Vehicles **5**(3), 1087–1103 (2023)
23. Nurullayev, D.: Emerging 5G networks and internet of things forensics. Cyber Law Rev. **1**(1) (2024)
24. Mahi, M.J.N., Chaki, S., Humayun, E., Imran, H., Barros, A., Whaiduzzaman, M.: A review on VANET security: future challenges and open issues. Indo. J. Electr. Eng. Inform. (IJEEI) **11**(1), 180–193 (2023)
25. Karabulut, M.A., Shah, A.S., Ilhan, H., Pathan, A.S.K., Atiquzzaman, M.: Inspecting VANET with various critical aspects–a systematic review. Ad Hoc Netw., 103281 (2023)
26. Al-Mekhlafi, Z.G., Al-Shareeda, M.A., Mohammed, B.A., Alayba, A.M., Saleh, A.M.S., Al-Reshidi, H.A., Almekhlafi, K.: Integrating safety in VANETs: a taxonomy and systematic review of VEINS models. IEEE Access (2024)
27. Farooqi, A.M., Alam, M.A., Hassan, S.I., Idrees, S.M.: A fog computing model for VANET to reduce latency and delay using 5G network in smart city transportation. Appl. Sci. **12**(4), 2083 (2022)
28. Upadhyaya, A.N., Shah, J.S.: Attacks on vanet security. Int. J. Comp. Eng. Tech. **9**(1), 8–19 (2018)
29. Zaidi, T., Faisal, S.: An overview: various attacks in VANET. In: 2018 4th International Conference on Computing Communication and Automation (ICCCA), pp. 1–6. IEEE (2018)
30. Mecheva, T., Kakanakov, N.: Cybersecurity in intelligent transportation systems. Computers **9**(4), 83 (2020)
31. Pethő, Z., Török, Á., Szalay, Z.: A survey of new orientations in the field of vehicular cybersecurity, applying artificial intelligence based methods. Trans. Emerg. Telecommun. Technol. **32**(10), e4325 (2021)

32. Algarni, A., Thayananthan, V.: Autonomous vehicles: the cybersecurity vulnerabilities and countermeasures for big data communication. Symmetry **14**(12), 2494 (2022)
33. Wu, H., Han, H., Wang, X., Sun, S.: Research on artificial intelligence enhancing internet of things security: a survey. IEEE Access **8**, 153826–153848 (2020)
34. Zhang, Z., Ning, H., Shi, F., Farha, F., Xu, Y., Xu, J., Zhang, F., Choo, K.K.R.: Artificial intelligence in cyber security: research advances, challenges, and opportunities. Artificial Intell. Rev., 1–25 (2022)
35. Zeadally, S., Adi, E., Baig, Z., Khan, I.A.: Harnessing artificial intelligence capabilities to improve cybersecurity. IEEE Access **8**, 23817–23837 (2020)
36. Horowitz, M.C., Allen, G.C., Saravalle, E., Cho, A., Frederick, K., Scharre, P.: Artificial intelligence and international security. Center for a New American Security (2022)
37. Gupta, R., Tanwar, S., Tyagi, S., Kumar, N.: Machine learning models for secure data analytics: a taxonomy and threat model. Comput. Commun. **153**, 406–440 (2020)
38. Xue, M., Yuan, C., Wu, H., Zhang, Y., Liu, W.: Machine learning security: threats, countermeasures, and evaluations. IEEE Access **8**, 74720–74742 (2020)
39. Shaukat, K., Luo, S., Chen, S., Liu, D.: Cyber threat detection using machine learning techniques: A performance evaluation perspective. In: 2020 International Conference on Cyber Warfare and Security (ICCWS), pp. 1–6. IEEE (2020)
40. Sirisha, G., Stephen, K.V.K., Suganya, R., Patra, J.P., Lakshmi, T.V.: An innovative intrusion detection system for high-density communication networks using artificial intelligence. Eng. Proc. **59**(1), 78 (2023)
41. Singh, K.U., Kumar, A., Varshney, N., Raja, L., Singh, T., Dewangan, A.K.: AI-driven security enhancements in wireless sensor networks. In: 2024 IEEE International Conference on Contemporary Computing and Communications (InC4), Vol. 1, pp. 1–7. IEEE (2024)
42. Abdi, A.H., Audah, L., Salh, A., Alhartomi, M.A., Rasheed, H., Ahmed, S., Tahir, A.: Security control and data planes of SDN: a comprehensive review of traditional, AI and MTD approaches to security solutions. IEEE Access (2024)
43. Naeem, M.A., Chaudhary, S., Meng, Y.: Road to efficiency: V2V enabled intelligent transportation system. Electronics **13**(13), 2673 (2024)
44. Karthiga, B., Durairaj, D., Nawaz, N., Venkatasamy, T.K., Ramasamy, G., Hariharasudan, A.: Intelligent intrusion detection system for VANET using machine learning and deep learning approaches. Wirel. Commun. Mob. Comput. **2022**(1), 5069104 (2022)
45. Ahmed, W., Di, W., Mukathe, D.: Privacy-preserving blockchain-based authentication and trust management in VANETs. IET Networks **11**(3–4), 89–111 (2022)
46. Luo, B., Li, X., Weng, J., Guo, J., Ma, J.: Blockchain enabled trust-based location privacy protection scheme in VANET. IEEE Trans. Veh. Technol. **69**(2), 2034–2048 (2019)
47. Lu, Z., Liu, W., Wang, Q., Qu, G., Liu, Z.: A privacy-preserving trust model based on blockchain for VANETs. IEEE Access **6**, 45655–45664 (2018)
48. Manimaran, P.: Ndnids: An intrusion detection system for ndn based vanet. In: 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring), pp. 1–5. IEEE (2020)
49. Bangui, H., Ge, M., Buhnova, B.: A hybrid machine learning model for intrusion detection in VANET. Computing **104**(3), 503–531 (2022)

Evaluating ML Models for Intrusion Detection in Network and VANET Security

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Abstract Vehicular Ad Hoc Networks (VANETs) are vital in improving safety, security, and overall quality of life in robust development of smart cities. VANETs are highly vulnerable to cyberattacks due to high mobility of vehicles and lack of central security control management. Intrusion Detection Systems (IDS) provides first layer of defense, which is mainly dependent on vehicle collaboration model for possible detection of cyber security threats. Unfortunately, many traditional IDS methods have shown poor performance due to corruption, leading to abnormal behavior and reduced effectiveness. The detection of emerging cyber security threats requires Machine Learning (ML) models. This paper presents the comparative performance analysis of ML algorithms to possibly detect cyber security threats in various computing environments with limited resources including embedded systems, IoT systems and VANETS. The work uses two well-known datasets namely benchmarked network dataset i.e.; NSL-KDD and VANET dataset i.e.; Erlangen for detailed evaluation of ML algorithms: Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbor (kNN), and Decision Tree (DT), Logistic Regression (LR). The performance evaluation is carried out on key performance measures including precision, recall, F1-score, and efficiency in computations. This paper presents *EdgeAnomSift*, a framework that divides the NSL-KDD dataset into smaller parts to evaluate model performance under different training conditions in a scalable way. Experiments with the NSL-KDD dataset show that DT and RF provides high rates of accuracy and efficiency in detecting attacks making it a best algorithm. KNN works well with datasets in smaller size but is ineffective for large computing. SVM is not suitable for real-time detection as it requires a lot of computing power. LR is resource-efficient but needs improvements for the detection of rare attacks. The results show that RF and DT are

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the best models for Intrusion Detection Systems (IDS) in VANET computing. LR and SVM need more improvement. Tests with the Erlangen dataset confirm that DT is the top choice for VANET security, followed by RF. These findings suggest that efficient ML models can help improve cybersecurity in vehicle networks. The study also explores practical uses, such as linking ML-based IDS with security tools like SNORT. It also suggests future research to enhance intrusion detection in dynamic vehicle systems.

Keywords VANETs · Resource constrained environment · ML algorithms · IDS

1 Introduction

Computer networks must be secured from unauthorized access and malicious behavior through strong security measures because of our increasing dependence on networked devices. Cyber-attacks like data leak unauthorized access, and cyberthreat are affecting the traditional security measures. Antivirus software, firewalls, and encryption provide a level of protection, but at the same time modern networks requires more efficient and adaptive security measures to counter emerging threats.

IDS is capable of monitoring all network task by identifying network intrusions, to identify anomalous behavior, alerting system administrators to take mandatory actions before substantial damage is done. The amount of network data continually increases with passage of time and demands for intelligent as well as efficient IDS, that can handle large-scale traffic while minimizing the risk of false positives and negatives [1].

The main aim behind effective IDS is to alert the system administrator about any suspicious activity by monitoring actions happening within the system [2]. The issue of protecting networks in resource-constrained contexts becomes more obvious as the number of devices linked to networks and network complexity keep on increasing, especially in areas like IoT and VANETs. Because of their limited memory, energy, and processing capabilities, VANETs—which allow wireless communication between vehicles for improved traffic management, automotive engineering, road safety, and autonomous driving—are especially vulnerable to cyber-attacks [3]. Traditional IDS solutions are often impractical in such environments due to the overhead they introduce; this calls for the development of (ML)-based IDS solutions that are computationally efficient, scalable, and lightweight.

ML techniques have widely known for their efficient performance in improving the effectiveness of IDS by providing adaptive learning skills and the capacity to identify previously unidentified attack patterns. In anomaly-based IDS solutions, ML algorithms can recognize patterns of normal behaviour by training, allowing the system to identify deviations that may indicate an intrusion However, there are particular difficulties when implementing ML algorithms in environments with limited resources, such embedded systems, VANETs, and Internet of Things devices.

These settings necessitate algorithms that maximise accuracy while simultaneously optimising processing time, memory utilization, and energy consumption.

The goal of the research investigation is to analyse the effectiveness of baseline machine learning algorithms in identifying network and VANET-specific threats, with an emphasis on how well they work in real-time, resource-constrained settings. In the context of IDS for resource-constrained systems, this work examines the performance of five well-known machine learning algorithms: DT, kNN, RF, SVM, and LR. Two important datasets used in this research: the NSL-KDD dataset for network attacks and the Erlangen City traffic dataset for VANET-specific attacks. we want to provide important insights into the algorithms' scalability, computational effectiveness, and detection precision in real-world situations through this research. This paper makes several key contributions:

1. An analysis of how well conventional algorithms for machine learning perform in contexts with limited resources, with a focus on memory utilisation, computation time, and scalability.
2. Deep investigations on ML algorithms' suitability for network and VANET security, emphasising how well they identify different kinds of cyberthreats and attacks.
3. A comprehensive evaluation of how well the algorithms function with different data sizes, with an emphasis on real-time IDS deployment in systems with limited resources such VANETs, edge devices, and embedded systems.

In later sections, there is details about existing research in the field of ML based IDS for resource-constrained systems, dataset's description and methodologies used in this study, present the experimental results, and interpret the significance of our findings for future IDS development in both traditional networked systems and emerging environments like VANETs.

2 Related Work

ML algorithms are highly effective and perform so well in the field of IDS, they have been utilised all over the world to detect malicious activity in networks. The task of an IDS is to alert the system administrator about any suspicious activities [4]. Machine learning helps in identifying and classifying security threats within IDS [5]. A hybrid intrusion detection system can be designed by combining ML techniques with conventional security procedures.

By applying appropriate machine learning algorithms, existing detection approaches can be improved in identifying and detecting assaults [6]. In one study, an Intrusion Detection System (IDS) was automatically constructed using Weka and RapidMiner. The NSL-KDD dataset was subjected to four classifiers: Random Forest (RF), Sequential Minimal Optimisation (SMO), Multi-Layer Perceptron (MLP), and Naïve Bayes (NB). According to the findings, RF provided the best accuracy. Because

Auto-WEKA can select the optimal classifier and settings automatically with minimal configuration, it was suggested.

Samawi et al. [7] A special hybrid model using the Random Forest-Recursive Feature Elimination (RF-RFE) method is proposed to improve the accuracy of IDS [8]. To further improve IDS performance, a hybrid ensemble model using RF-RFE was introduced. The effectiveness of classifiers was evaluated based on accuracy, error rates, response time, recall, precision, and F1-score [9]. When comparing classifiers, the Decision Tree worked faster than Naïve Bayes but was less accurate and had more errors. An experiment was done using the NSL-KDD dataset in WEKA to test different ML algorithms. Among them, RF performed the best, reaching a precision rate of 98.6% [10]. Various algorithms were used to classify attacks and find the most effective method for predicting and identifying security threats [11]. However, algorithms, specifically DL models, require high processing power and large amounts of data, making their use challenging in resource-limited environments. The issue of its usefulness in environments with limited resources remains unresolved. Few researchers are focusing on this element in the literature, with an emphasis on deployment in mobile devices like smartphones, a number of efficient neural networks (NNs) have been created, including Once-for-All [12], ShuffleNet [13], EfficientNet [14], and MobileNet. These deep learning models signify a change from focusing only on accuracy to taking model complexity into account. While some of these networks assess efficiency by counting MACC (Multiply-Accumulate) operations, others are optimised to minimise the amount of weights and biases. For example, Cai et al. [15] suggest a more sophisticated heuristic by creating a prediction technique called Neural Power that calculates the energy usage of each layer and adjusts the network appropriately. This research concentrates on optimizing neural networks, which already need a lot of resources. Additionally, models are optimized in terms of their design and calculations using the methodologies that have been explained. In order to bridge this gap, we are investigating the effects of different data sizes in the constraint-restricted context rather than optimizing model computation. Instead of using deep learning models for this, we employed traditional machine learning methods. Table 1 presents a summary of the literature survey of systems requires further investigations into variable-sized datasets. Hence evaluating the effectiveness of ML algorithms across both small and large-scale systems is the basic requirement of this study.

The use of the NSL-KDD dataset for IDS that address performance and adaptability issues in resource-constrained environments is the main topic of this comparative study of several research papers. Another gap is real-time adaptability as models need to adjust for progressing instances, including embedded system. Research including comparison of multiple datasets (e.g., UNSW-NB15 vs. KDDCup99 or NSL-KDD) reveals the adaptability for effective deployment in environments with changing data constraints and features. This analysis emphasizes the need to evaluate machine learning (ML) algorithms scale able data sets ranging from small, medium to large data set. The proposed method is essential for understanding how different machine learning models behave in settings with limited resources, particularly when continuous learning is required. Model training and retraining efficiency

Table 1 Related Work

Study	Research focus	Dataset used	Algorithm used	Detected intrusions	Gap Identified for resource-constrained systems
[16]	Optimized multi-stage ML framework for IDS	NSL-KDD	SVM, RF, KNN	DOS, Probe, U2R, R2L	Calls for lightweight, scalable models for real-time IDS in resource-limited environments
[17]	Particle swarm optimization (PSO) for IoT-based IDS	NSL-KDD	PSO, SVM	Probe, U2R, DOS	Highlights need for efficient, IoT-compatible models to reduce computational load
[18]	Feature selection optimization for IDS	NSL-KDD	Feature selection, KNN	DOS, Probe	Requires resource-efficient solutions for embedded IoT deployments
[19]	Neural networks and nearest neighbors for IDS	NSL-KDD	CNN, KNN	R2L, U2R, DOS	Suggests lightweight NN models for real-time use
[20]	For cloud-based IDS classification algorithms are evaluated	NSL-KDD	WEKA (various classifiers)	DOS, Probe, R2L	Emphasizes need for models that perform well on smaller data subsets for cloud scalability
[21]	Supervised discretization to enhance classifier performance	NSL-KDD	WEKA	DOS, R2L, Probe	Suggests adaptive classification for dynamic systems
[22]	Comparison of IDS models with focus on NSL-KDD	NSL-KDD	WEKA, SVM, DT	Probe, U2R	Notes gap in adaptability for constrained, real-time systems
[23]	Comparison of datasets for IoT-focused IDS	NSL-KDD, KDDCup99	KNN, SVM, NB	U2R, DOS, Probe	Suggests optimized, adaptable models for embedded systems
[24]	SVM-based IDS model evaluation	NSL-KDD, KDDCup99	SVM	Probe, DOS	Highlights need for scalable, resource-efficient SVM models
[25]	Comparison of UNSW-NB15 and NSL-KDD for IDS	NSL-KDD, UNSW-NB15	RF, NB	DOS, R2L	Adaptive IDS for real-time, embedded environments needed

(continued)

Table 1 (continued)

Study	Research focus	Dataset used	Algorithm used	Detected intrusions	Gap Identified for resource-constrained systems
[26]	Classification performance on NSL-KDD	NSL-KDD	WEKA	DOS, R2L, Probe	Need for real-time, adaptive intrusion detection in embedded systems
[27]	Focus on detecting rare-class attacks in IDS	NSL-KDD	Decision trees, NB	U2R, R2L	Low-memory, adaptive systems for rare event detection needed

is critical in situations that need continuous learning, such real-time threat detection in dynamic networks. This calls for a thorough examination of machine learning techniques on medium-sized datasets in order to balance computational expense and learning efficacy. Models that can learn incrementally on tiny datasets are more suited for situations that need frequent updates, according to studies comparing dataset subsets.

3 Methodology

To ensure the effectiveness of the conventional light weight machine learning algorithm across different domains inn constrained restricted environment we analyzed it across two different network traffic NSL-KDD [28] and Erlangen dataset [29] for VANETs. Sections 3.1 and 3.2 contains the detailed workflow of these case studies.

3.1 Workflow of Network Attack Detection Using NSL-KDD

The proposed framework, called EdgeAnomSift, is shown in Fig. 1. It follows a step-by-step process divided into four main phases using the NSL-KDD dataset. This framework is designed based on a case study of Sybil attack detection to ensure its usefulness in real edge-based systems. The framework follows four main phases. First, preprocessing is performed to prepare the NSL-KDD dataset for analysis. Next, data splitting is done by dividing the KDDTrain+ dataset into five parts of different sizes. After that, training takes place, where ML algorithms are trained on each data split. Finally, testing is conducted to check the output of the trained models.

In WEKA, the KDDTrain+ dataset was split into five parts for training. Each part was tested using technique named as tenfold cross-validation, which helps measure the error rate of learning techniques, which involves the segmentation of the dataset into ten equal parts. The training and testing is repeated ten times, with each part

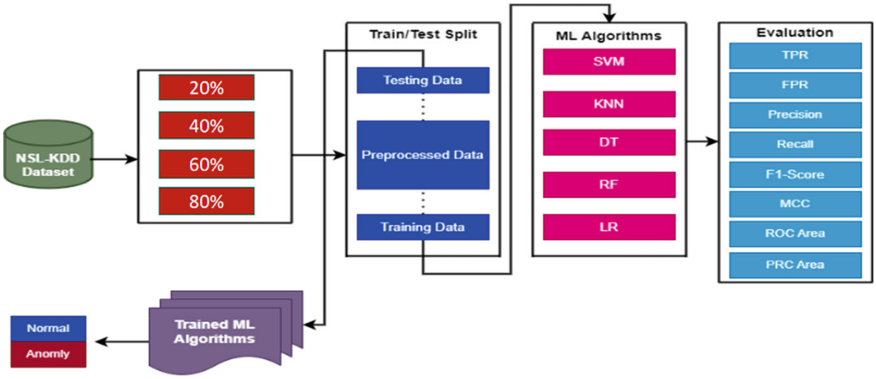

NSL-KDD Dataset
20%
40%
60%
80%
Train/Test Split
Testing Data
Preprocessed Data
Training Data
ML Algorithms
SVM
KNN
DT
RF
LR
Evaluation
TPR
FPR
Precision
Recall
F1-Score
MCC
ROC Area
PRC Area
Trained ML Algorithms
Normal
Anomly

Fig. 1 EdgeAnomSift framework

used once for testing and the rest for training. This ensures a fair evaluation of the ML models.

In training, one part of the dataset is set aside, and the error rate is measured on this unused part while the model is trained on the remaining nine parts. Repeat the process ten times, with each part taking a turn as the test set. After all ten rounds, the average error rate is calculated to determine the overall performance [30]. For testing, the entire KDDTest+ dataset was used to evaluate each machine learning model trained on the different splits of KDDTrain+.

3.2 Workflow of VANETs Attack Detection Using Erlangen City

Figure 2 shows the workflow for datasets used in VANETs. The process has several steps: (1) downloading the dataset from GitHub as a.csv file, (2) converting unlabeled data into labeled data, (3) for training and testing split the dataset to classify normal and malicious (Sybil attack) instances, and (4) applying machine learning algorithms to evaluate performance.

3.3 Dataset Details

Following datasets have been used for simulation purposes:

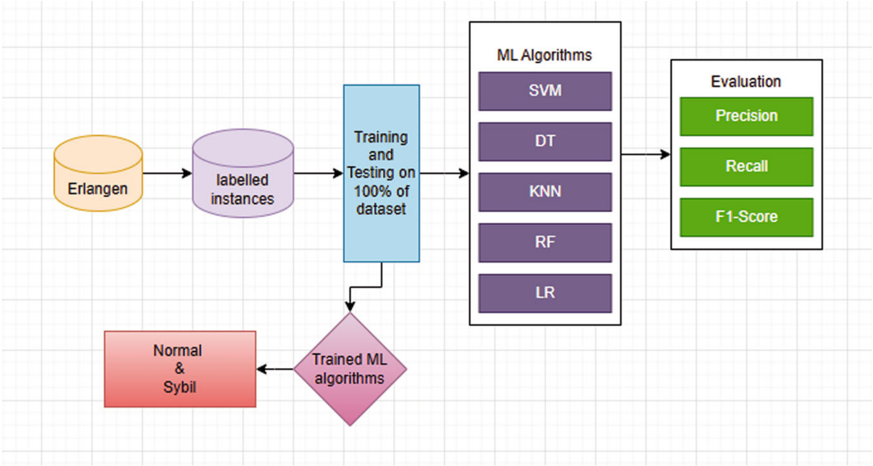


Fig. 2 Framework for Sybil attack detection in VANET

3.3.1 NSL-KDD Based on Network Traffic Attacks

The KDD Cup has been upgraded with the NSL-KDD. KDD Test+, KDD Train, KDD Test-21, and KDD Train-20% are its four components. Files of various network attacks that an IDS must identify in order to stop security risks are included in this dataset. There are 42 features in each file, 41 of which are associated with network traffic and the last one is the class label.

The dataset includes four main types of attacks: Remote to Local (R2L), Probe, Denial of Service (DoS), and User to Root (U2R) [8]. It is widely used for testing IDS performance and is available on Kaggle. The dataset comes with predefined training and testing sets to ensure fair evaluation of IDS methods. To train models training set is used, while the testing set helps measure their performance on new data. Table 2 presents the distribution of real and unreal instances in selected datasets.

3.3.2 Erlangen City Dataset for Vehicle Ad Hoc Network Dataset

The dataset that is used as an application to demonstrate the effectiveness of ML algorithms in resource constrained system for VANETs as case study. The dataset of Erlangen, city of Germany, generated from the simulation tool SUMO in which various cars send requests to a single car. The requests initiated by the sender cars to one receiver car consist of start and end time. The dataset was initially downloaded from GitHub as.csv file that consist of unsupervised data, this contains all the traces having fields such as number of packets, start time, end time, rate (packets per second), time period, actual distance between receiver and sender, sender stopping distance, receiver stopping distance, and severity of the request. This dataset was then converted into labelled dataset for the detection of sybil attack. Sybil attack has

Table 2 Dataset details

Parameters	Description
Source	NSL-KDD dataset from Kaggle.com
Description	Refined and improved version of the KDD 1999, for training and testing of Network Intrusion Detection System (NIDS)
Number of instances	KDDTrain+: 125,973 KDDTest+: 22,544
Number of features	42 (41 input features + 1 class label)
Class (target)	– Normal Types of attacks: 1. DoS 2. Probe 3. R2L 4. U2R
Classes distribution	– Normal: real traffic – Anomaly: malicious traffic or data having non-real instances

been detected based on parameters like high-rate value, large distance values, and unrealistic values for both receiver and sender stopping distance and high packets count.

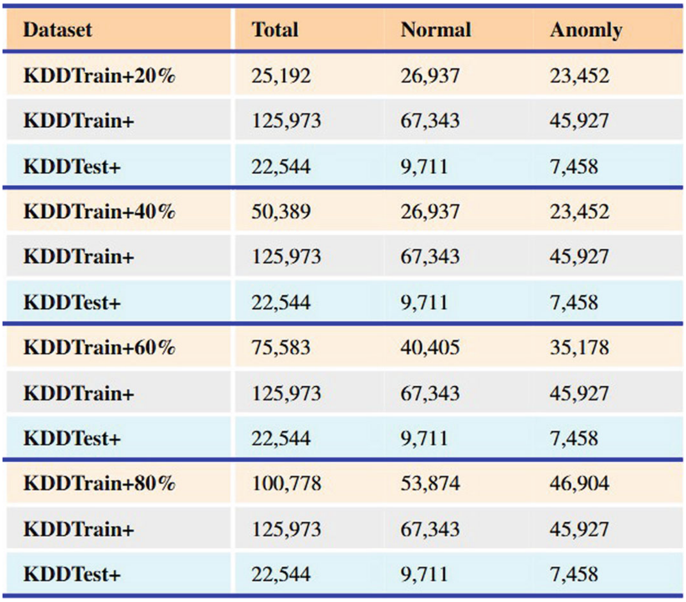
3.4 Data Preprocessing

To guarantee the quality of data, accuracy, integrity, and consistency are three crucial components. However, there are many inaccurate, lacking, and inconsistent data in real-world databases and data warehouses. Considering the fact that data preparation can eliminate unnecessary information from so much raw data. Information unrelated to modeling, which can not only lower the data's dimension while simultaneously quickening the training rate of the model [17]. ML algorithms can be selected from the classify panel following data preprocessing. WEKA supports classifiers like KNN, C4.5 (decision trees), RF, SVM, and Logistic for both categorical and numerical predictions.

Preprocessing: Before training the models, it is important to prepare the data by normalizing values, selecting key attributes, and handling missing data. WEKA provides several tools for this process.

Resampling: The resampling of KDD Train + 1 has been done on weka and presented in Fig. 3. The total number of available instances was 125,973 which have 42 attributes divided into 20%, 40%, 60% and 80%.

Model Training: WEKA provides simple ML methods like DT, LR, RF, KNN, and SVM. Users can train these models using labeled datasets that contain network traffic details. WEKA offers two ways to train models: one is cross-validation and



Dataset	Total	Normal	Anomly
KDDTrain+20%	25,192	26,937	23,452
KDDTrain+	125,973	67,343	45,927
KDDTest+	22,544	9,711	7,458
KDDTrain+40%	50,389	26,937	23,452
KDDTrain+	125,973	67,343	45,927
KDDTest+	22,544	9,711	7,458
KDDTrain+60%	75,583	40,405	35,178
KDDTrain+	125,973	67,343	45,927
KDDTest+	22,544	9,711	7,458
KDDTrain+80%	100,778	53,874	46,904
KDDTrain+	125,973	67,343	45,927
KDDTest+	22,544	9,711	7,458

Fig. 3 Attack and normal instances in NSL-KDD dataset

the other is percentage split. The percentage split method divides the dataset into separate parts for training and testing, while cross-validation splits it into multiple sections for a more reliable evaluation. Before training and testing, class labels must be set [31].

Cross-Validation: WEKA has built-in tools for cross-validation that help check how well a model works on new data.

Performance Metrics: System results performance measures including accuracy, F1-score, recall, precision, and the Area under the Receiver Operating Characteristics Curve (AUC). These help users understand how well an IDS can detect threats.

3.5 T_SNE Plot for KDDTrain+

An unsupervised non-linear feature reduction algorithm for visualizing and exploring is called t- SNE (t-distributed Stochastic Neighbor Embedding). By assigning a position to each data point on a 2-dimensional or 3-dimensional map, the t-SNE technique helps visualize high-dimensional data by minimizing the tendency for dots to be crowded together and producing better organized data visualizations. It has been demonstrated that t-SNE can both disclose a global structure in the high dimensional data and capture a large portion of its local structure [32]. Figure 4 shows the t-SNE plot of KDDTrain+ dataset. The plot illustrates that, the normal

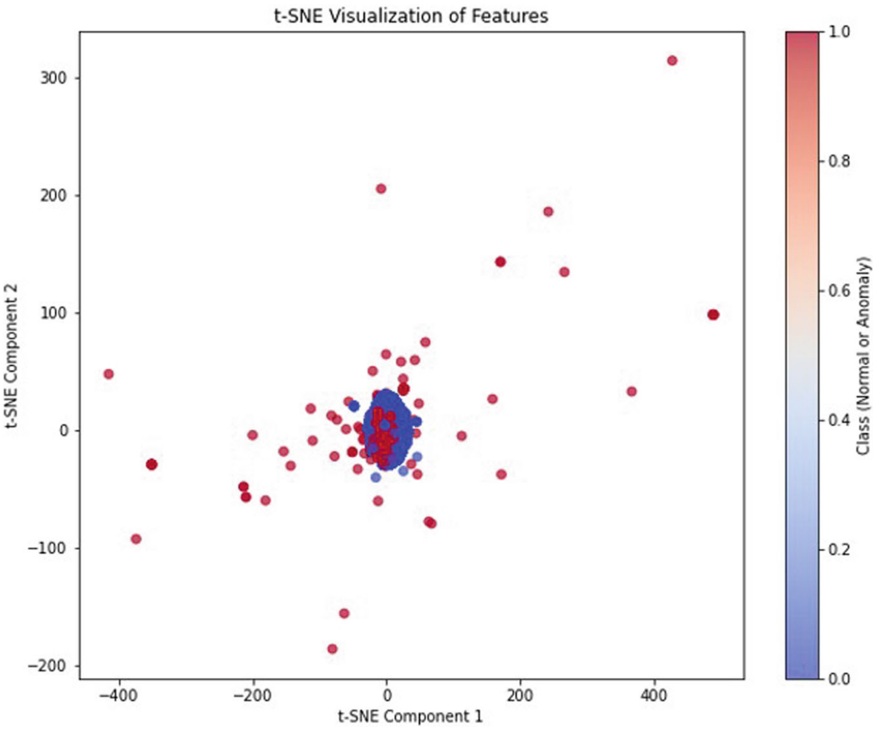


Fig. 4 t-SNE plot

and anomaly classes exhibit significant overlap at certain points, highlighting the inherent complexity and non-linear separable within the dataset.

3.6 Supervised Machine Learning (ML) Algorithm

To identify the learning models that perform well in constrained environments, our study utilizes SVM, Logistic Regression, and Random Forest. These models require fewer parameters compared to recent deep learning models, do not require pre-training, and are less time-consuming. The aim is to further analyze which of these models is most suitable for specific situations. Regression and classification. While regression predicts a category to which the data belong, classification predicts a numerical value derived from earlier data observations [33].

3.6.1 Decision Tree

ML algorithm, DT classify network traffics as harmful or safe using in an IDS. This classification is based on different factors like protocol type, source and destination IP addresses, and port numbers. DT is useful because they can handle both numbers and categories effectively. They work by categorizing the dataset into micro groups step by step, based on the values of these features [34].

3.6.2 Random Forest

This machine learning algorithm built multiple decision trees during training. Random forest proves to be highly effective for information derivation due to its capability of handling huge and complex datasets and its resistance to over fitting and hence contributes to IDS effectively [35].

3.6.3 K-Nearest Neighbor

KNN is a simple method that classifies data by comparing it to known examples from a training set. In an IDS, KNN detects unusual network activity by matching its features with previously identified cases. Its straightforward and flexible design makes it one of the most commonly used ML techniques for classification tasks [36].

3.6.4 Support Vector Machine

SVM is utilized for regression and classification tasks, it is a supervised ML method. Its foundational approach is finding the best boundary, called a hyperplane, to separate data points into different groups. SVM helps in distinguishing normal and harmful network traffic by creating a clear separation between the two in IDS. It is especially useful when data is not easily divided in a straight line [37].

3.6.5 Logistic Regression

A statistical method for binary classification is called LR. In an IDS, it helps predict whether a network event is harmful or safe. This method works best when there is a direct or nearly direct relationship between the input features and the expected outcome [34].

4 Experimental Setup

This section presents a series of experiments conducted on DESKTOP i5-3470S CPU @ Intel(R) Core (TM) 2.90 GHz 2.90 GHz having 8.00 GB of RAM to assess the performance of our approach of dividing the dataset into various sizes for understanding how different ML models behave in settings with limited resources, particularly when continuous learning is required. Model training and retraining efficiency is critical in situations that need continuous learning, computational expense and learning efficacy. Models that can learn incrementally on tiny datasets are more suited for situations that need frequent updates, according to studies comparing dataset subsets.

4.1 Performance Parameters

This study focuses on evaluating the performance of each algorithm using different assessment measures. The analysis examines several parameters, including Precision, True Positive (TP) rate, False Positive (FP) rate, Recall, F-measure, Matthews Correlation Coefficient (MCC), PRC area, and ROC area.

(i) Accuracy: The percentage of correct or true predictions are determined here. The accuracy is calculated using a formula based on the Confusion Matrix, the total number of instances are represented by n in following equation.

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{n} \tag{1}$$

(ii) F-Measure: Also known as the F1 score where two metrics precision and recall are combined by taking their harmonic mean into a single value. It provides a balanced measure of a test's accuracy.

(iii) MCC: The MCC measures the quality of binary classifications, particularly with unbalanced data. It considers TP, FP, TN and FN. perfect prediction is determined by $+1$, predictions are no better than random when the value is 0, and -1 shows complete disagreement between the prediction and the actual result.

(iv) ROC Area: The ROC Area evaluates a classifier's performance across different threshold settings. The AUC, a single figure that represents overall performance, is frequently used to summarise it [38]. The ROC curve compares the TP rate (sensitivity) against the FP rate (1-specificity) for a range of threshold settings; higher values suggest superior performance. The ability of a model to distinguish between positive and negative classes is determined by AUC of ROC. Similarly, the Precision-Recall Curve (PRC) is used to evaluate binary classification models by plotting precision (positive predictive value) against recall (true positive rate) across different thresholds. Higher PRC values also signify better performance. The AUC-PR gives a single value of the model's ability to balance recall and precision across various thresholds.

(v) TPR: Since accuracy and true positive rate are the same, we haven't taken this metric into account.

(vi) FPR: The formula to determine False Positive Rate is,

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{TN} + \mathrm{FP}} \tag{2}$$

(vii) Recall: It is the percentage of positive class instances that are accurately expected to be positive.

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{3}$$

(viii) Precision: It is a metric that calculates the likelihood that a positive forecast will come true.

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{4}$$

5 Experimentation

The Figs. 5, 6, 7, 8, 9, 10, 11 and 12 displays the testing results of Performance parameters discussed in above section.

In Figs. 13 and 14, memory and time consumption by ML algorithms are shown. In left panel memory utilized by each algorithm in MB varies with change in size of dataset. For small portion of dataset say 20% RF consumes more memory whereas DT utilizes least. Whereas DT consumes least memory in this scenario. LR and DT maintains stable and minimal memory consumption across all splits, making it suitable for large-scale setups. The unpredictable behavior of SVM with RBF and polynomial kernels indicates possible instability in resource management. In right panel time consumption by each algorithm in seconds varies with training split. RF, LR and DT increases linearly with the training split size for all models, are the fastest to train, requiring minimal computational time. SVM consumes large amount of time with increase in training split proves to be slowest among all. Decision Trees stand out as the best option for real-time adaptability with minimal resource strain.

The analysis of ML algorithms on varying sized dataset provide key insights regarding their suitability for continuous learning systems and multi-size setups. DT has the highest values in Precision, Recall, and F-score across all dataset sizes consistently, with notable performance peaks at 20 and 60% dataset subsets. This indicates that DT excels in effectively identifying both real and unreal instances, making it suitable ML model for intrusion detection in resource-constrained environments. RF algorithm exhibited high stability and strong performance, due to its ensemble

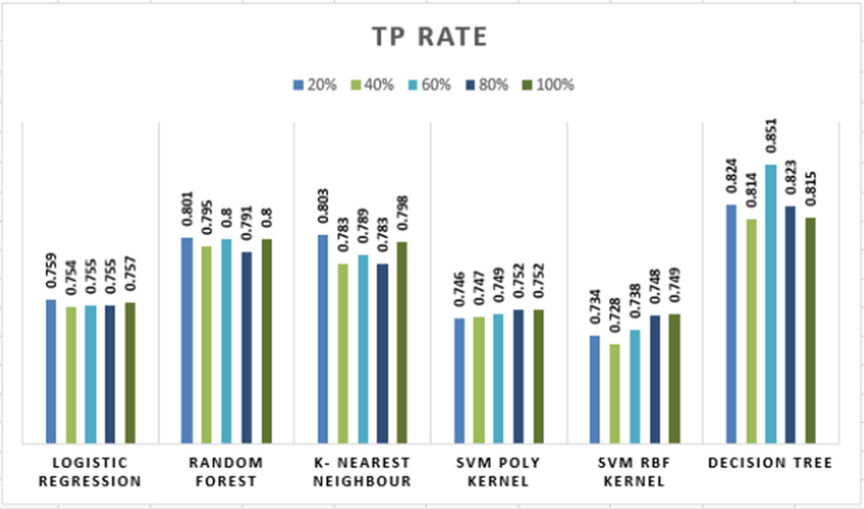


Fig. 5 TPR for ML models on each split

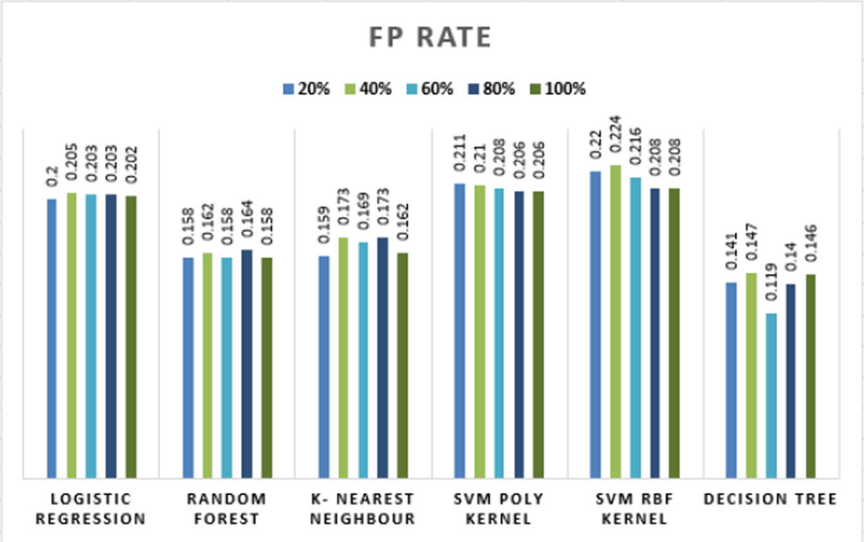


Fig. 6 FPR for ML models on each split

nature, particularly in larger datasets. The capacity of RF to reduce over fitting by averaging predictions over multiple decision trees helps in balancing outcomes as it performed better in ROC Area and PRC Area than others, highlighting its flexibility in distinguishing between attack and normal instances, hence highly recommended for real-time systems requiring stable performance. SVM and LR performed relatively

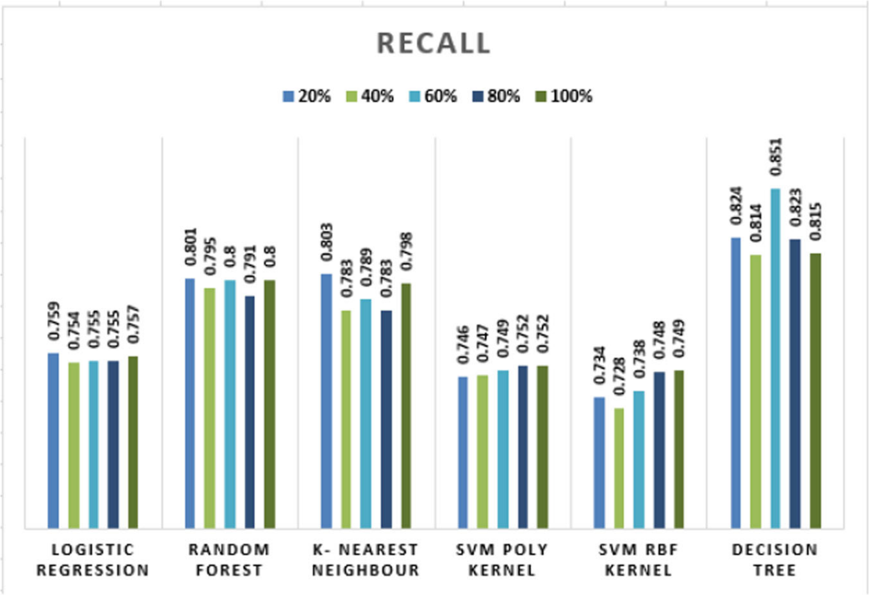


Fig. 7 Recall for ML models on each split

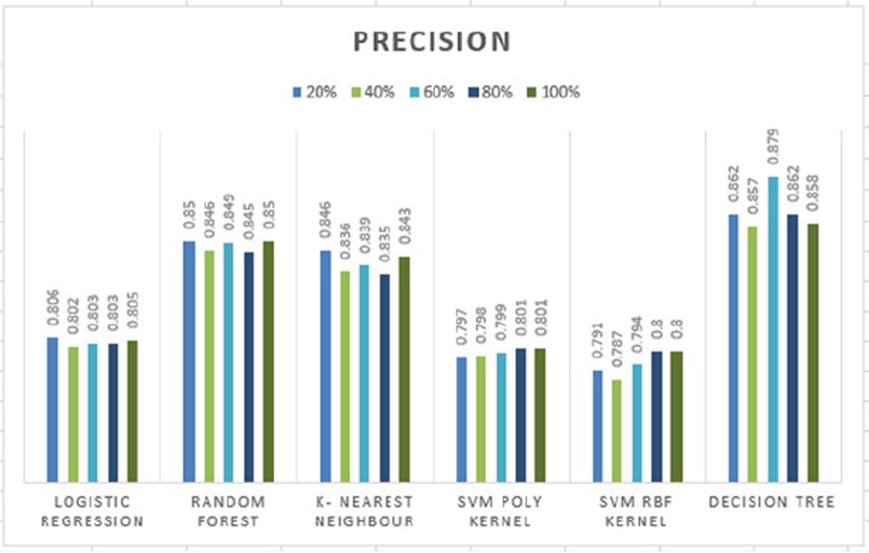


Fig. 8 Precision for ML models on each split

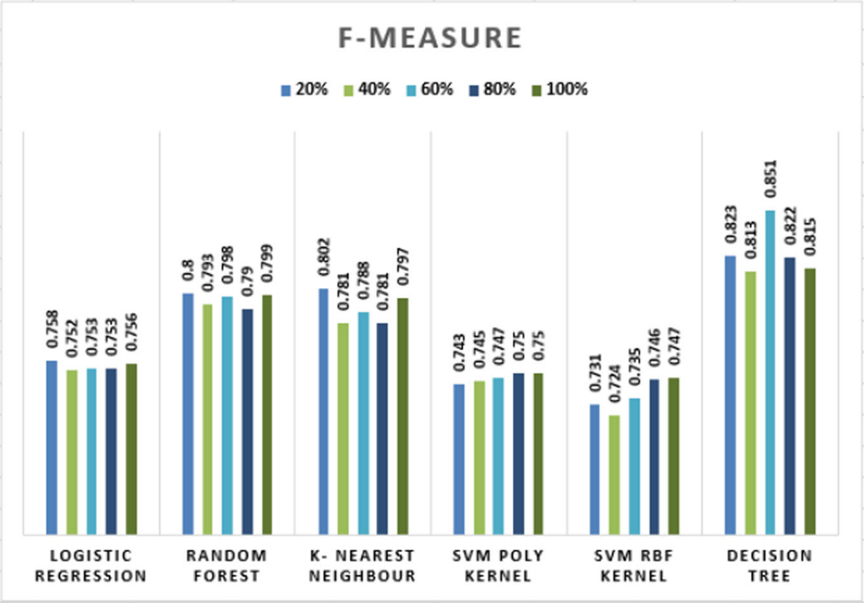


Fig. 9 F-measure for ML models on each split

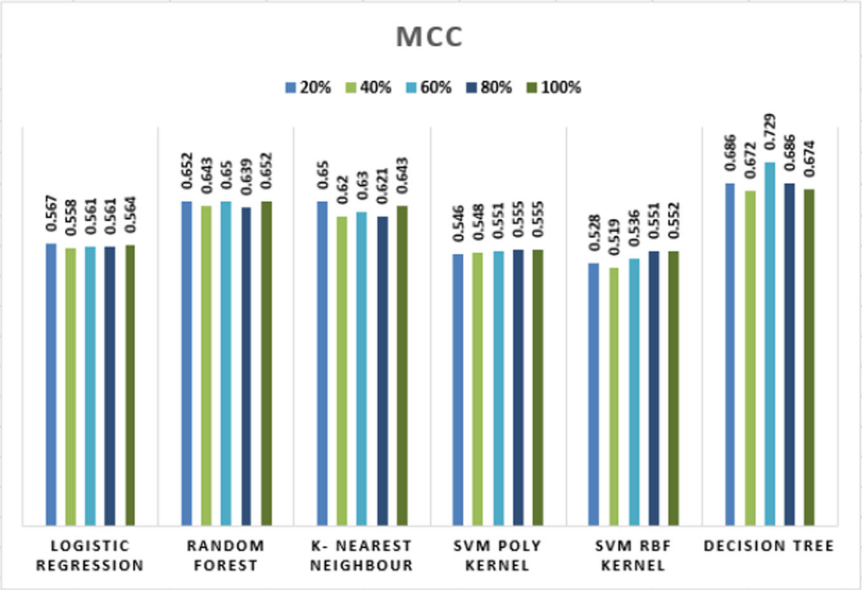


Fig. 10 MCC for ML models on each split

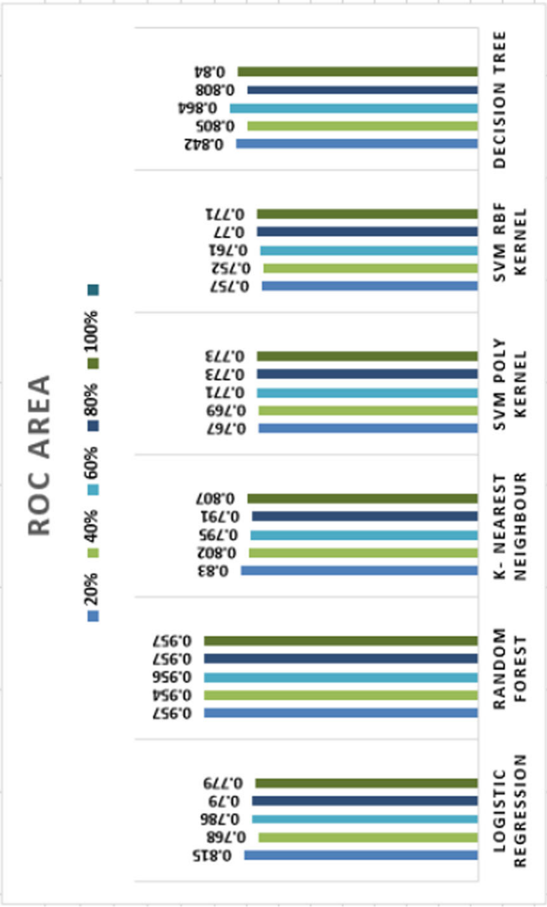


Fig. 11 ROC area for ML models on each split

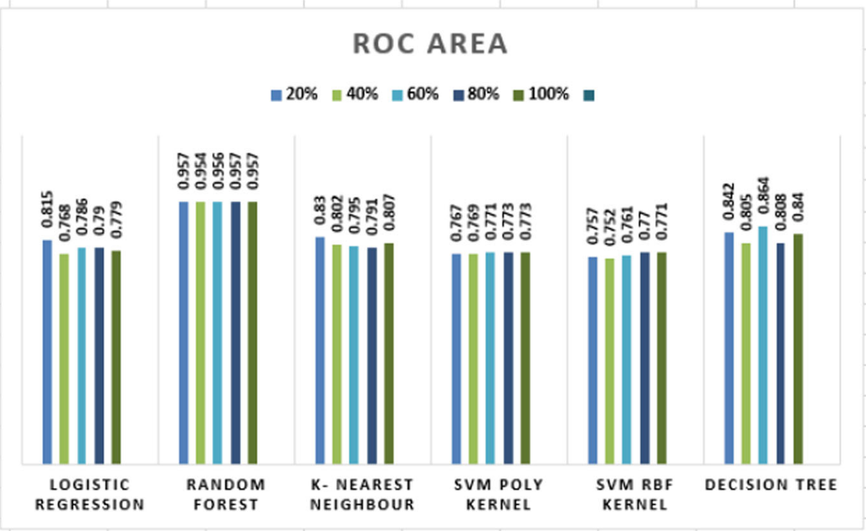


Fig. 12 PRC area for ML models on each split

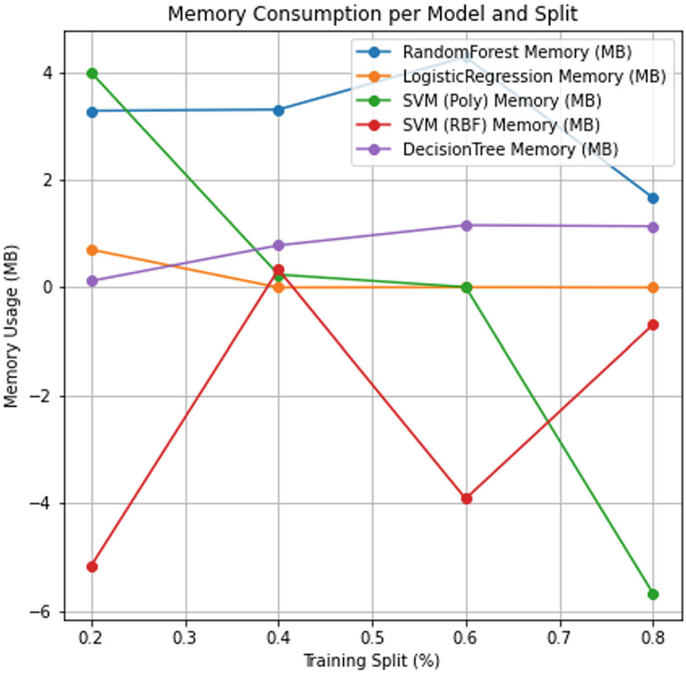


Fig. 13 Memory consumption by ML model

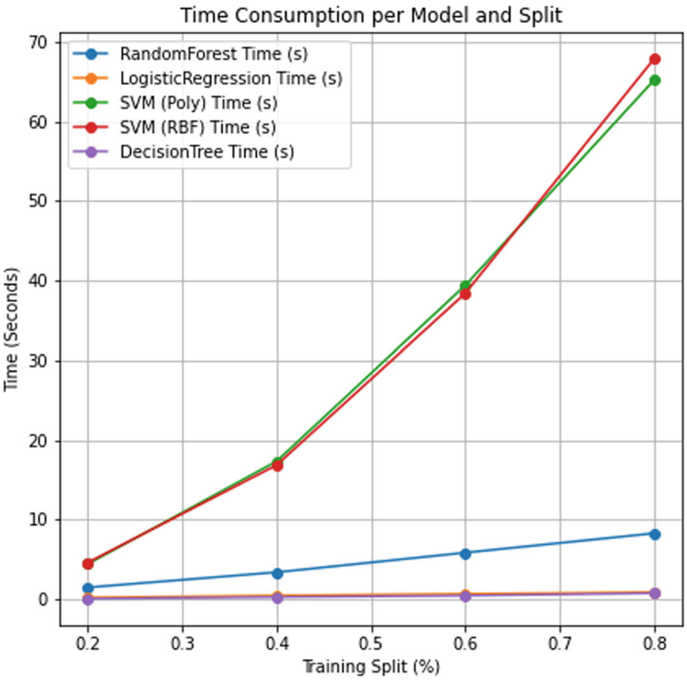


Fig. 14 Time consumption by ML model

poorly in terms of Recall and Precision, especially with smaller datasets (20 and 40%) and struggled to effectively identify rare attack instances, which is critical in intrusion detection systems dealing with imbalanced datasets. The lower values of F-scores of SVM and According to LR, these models must choose between preventing false positives and identifying attack events. Additionally, both models showed suboptimal MCC values, reflecting their challenges in balancing true positive and true negative predictions. Although SVM and KNN displayed moderate results in ROC Area and PRC Area, they were less effective in differentiating attack from normal traffic compared to DT and RF. Overall, DT and RF are the most robust and reliable classifiers for intrusion detection, particularly in continuous learning setups. While SVM and LR require further tuning to be considered suitable for identifying rare attack instances, their lower performance across multiple metrics highlights the need for more specialized approaches when dealing with imbalanced datasets in intrusion detection systems. Figures 15, 16, 17 and 18 presents Box plots, a straightforward yet effective graphing method, to accomplish required objectives. The median, which is not always central, is shown by a line inside the box. Plots can be orientated either vertically or horizontally; in this case, we employ horizontal boxes to keep the orientation consistent with the associated sample distributions [39]. Box plots split the data into segment that contains 25% of the data in that set. the analysis reveals that Decision Trees consistently outperform other models across all metrics, including TPR,

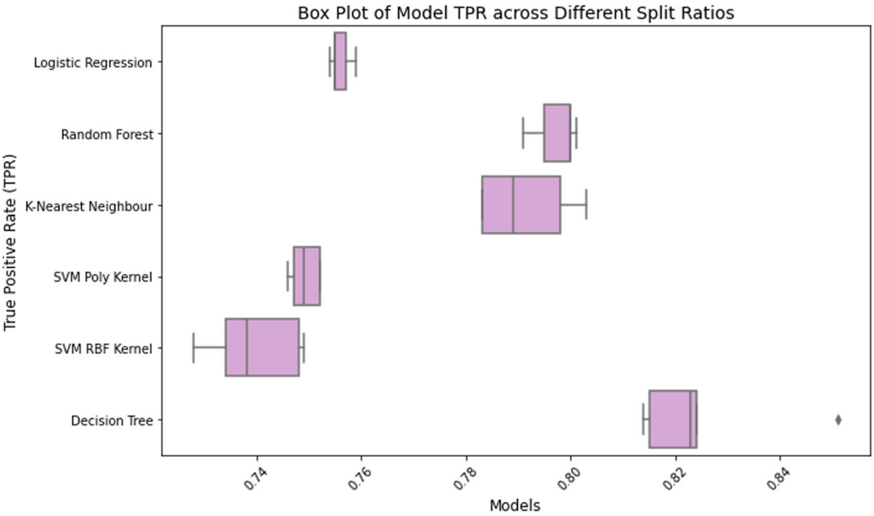


Fig. 15 TPR box plot

FPR, precision, and recall, making them the most reliable choice for both small-scale and large-scale setups. Random Forests and K-Nearest Neighbors are good alternatives, offering balanced performance with slightly higher variability. SVM models, particularly the Polynomial Kernel, demonstrate lower effectiveness and greater variability, making them less suitable for resource-efficient or high-precision tasks. Logistic Regression, while stable, lags in key metrics like precision and recall, limiting its applicability to tasks requiring high classification accuracy. Decision Trees stand out as the best choice for robust and consistent performance across diverse scenarios.

Figures 5, 6, 7 and 8 display the testing results for the performance parameters discussed in the previous section, for a deep analysis of how ML algorithms perform across different size of dataset, results reveals that the DT achieves the highest values across all dataset sizes, with performance peaks at 20% and 60% data subsets. The model's simplicity and ability to effectively capture patterns, especially when the size of dataset is small. Its efficient performance, particularly in terms of Recall, Precision, and F-score, make it as an ideal choice for environments requiring stable performance under continuous learning or dynamic data environments.

The RF, benefits from its inherent ability to reduce over fitting by averaging predictions across multiple trees, being an ensemble of decision trees. As a result, RF demonstrates stable outcomes across all dataset sizes, maintaining relatively high values in Precision, Recall, F-score, and versatility are crucial. On the other hand, SVM—particularly with both polynomial and RBF kernels—struggled to deliver competitive results, especially in terms of Recall and Precision.

The SVM in an imbalanced dataset, might need further tuning to improve its ability to correctly identify rare attack instances, especially. Although it performs

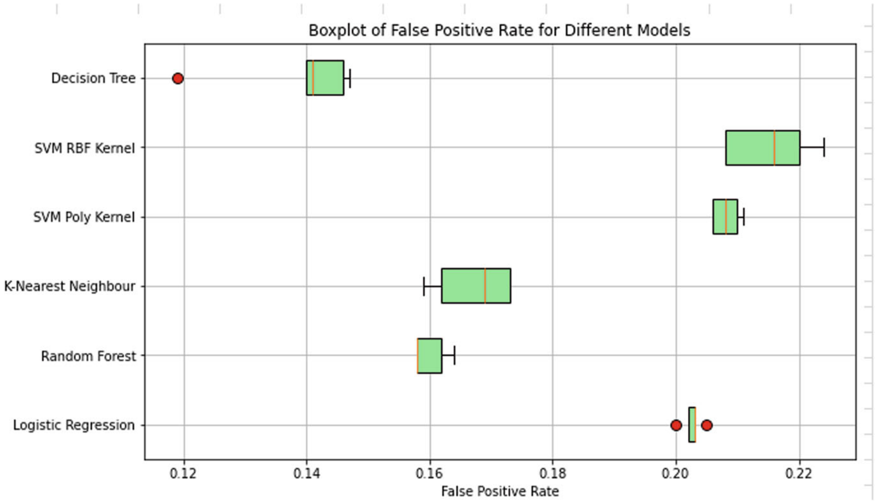


Fig. 16 FPR box plot

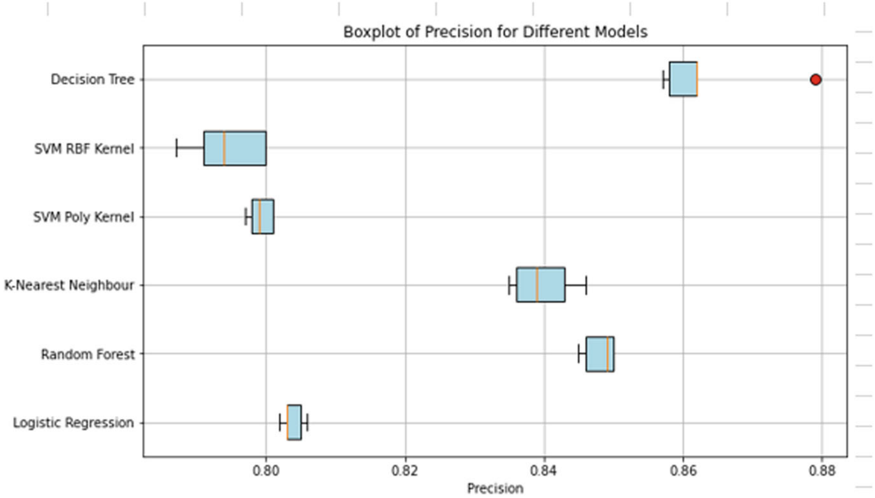


Fig. 17 Precision box plot

good in ROC Area and PRC Area, but gives lower values in TPR and F-score, essential in distinguishing between normal and attack instances, particularly with smaller datasets or those with unbalanced class distributions.

LR gives poor performance in Recall and Precision, which indicates it to be ineffective in identifying the minority class (anomalies or attacks) without further optimization. It had strong generalisation abilities on bigger datasets,but in sparse data it is inefficient to detect real and real data. RF and DT both models perform really

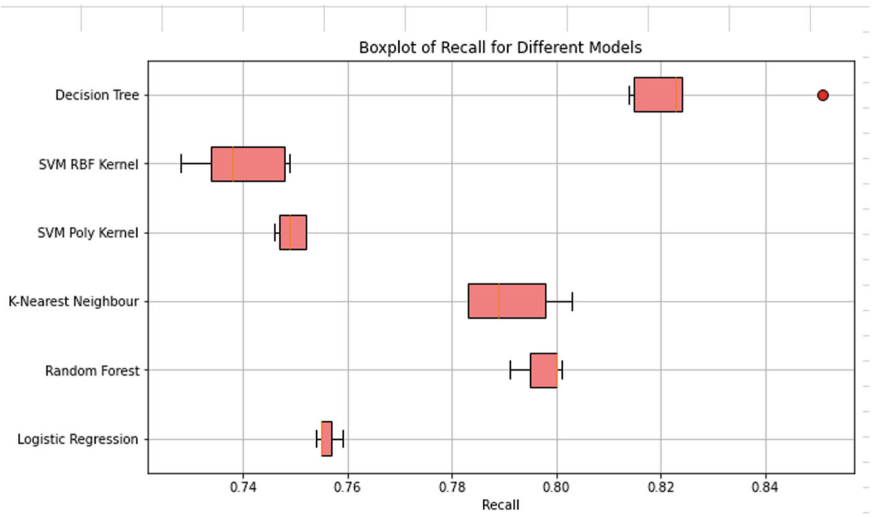


Fig. 18 Recall box plot

well in terms of ROC Area and PRC Area demonstrating their potential as reliable classifiers for intrusion detection tasks, in terms of model flexibility and scalability. Higher TPR and F-scores were regularly displayed by these models, demonstrating their capacity to detect valid attacks while reducing false positives. These models also had higher MCC values, demonstrating their capacity to successfully balance actual positives and negatives. On the other hand, SVM and KNN, provides slightly lower values for both precision and recall, indicating potential challenges in their ability to detect attack patterns in varying dataset sizes. Their lower PRC Area and ROC Area values suggest a reduced ability to distinguish between normal and attack instances effectively.

The detailed analysis of ML algorithms on different size of dataset, displayed and discussed above conclude that effective models for IDS are RF and DT, especially when stable performance is required. These models provide balanced performance across a range of metrics, including Precision, Recall, F-score, and MCC. The lower performance of SVM and KNN in identifying between normal and attack instances highlights the need for further tuning or more complex methods, especially in unbalanced datasets or smaller subsets.

Table 3 Outcomes of ML models

Model name	Precision (normal)	Precision (Sybil)	Recall (normal)	Recall (Sybil)	F1-score (normal)	F1 score (Sybil)	Time (s)	Memory (MB)
Logistic regression	0.67	0.88	0.81	0.77	0.73	0.82	0.59	2.18
Random forest	0.85	**0.92**	**0.85**	0.92	**0.85**	**0.92**	0.29	0.96
SVM	0.74	0.81	0.63	0.88	0.68	0.84	0.23	1.25
Decision tree	**0.88**	0.90	0.81	**0.94**	**0.85**	**0.92**	**0.00**	**0.01**
K-NN	0.64	0.81	0.67	0.79	0.65	0.80	**0.09**	0.79

5.1 Experimentation on ML Models Using Datasets for VANETs (Erlangen)

VANETs have scarce resources like low memory, energy, and computing power making it a good choice for using ML algorithms in resource constrained environments. To detect attacks, a real-world VANET dataset was obtained from the well-known platform GitHub; this dataset was created from a city (Erlangen) simulation in Germany, the dataset initially contained unlabeled data, which was then converted into labeled data. Figure 19 illustrates the sybil attack where distribution of data points across the axis are shown in red and blue dots. Sybil attacks are represented by red dots and blue dots represents normal instances. Furthermore, machine learning algorithms were applied to Erlangen dataset to evaluate parameters such as precision, recall, F1-score, time usage, and memory usage. The outcomes of ML algorithms are shown in Table 3 and Fig. 20.

Table 3 and Fig. 20 shows that the values of baseline ML models varies considerably across the different measures. The DT model performs the best, achieving F1-scores of 0.85 for real traffic and 0.92 for Sybil attacks with less possible units of time and very little memory (0.01 MB). The values of RF model reveals its best performance with similar F1-scores, but it uses slightly more resources (0.29 s and 0.96 MB). K-NN model on the other hand delivers the poorest performance, with F1-scores of 0.65 for real traffic and 0.80 for Sybil attacks, and consumes less time (0.09 s), though its memory usage is efficient (0.79 MB).

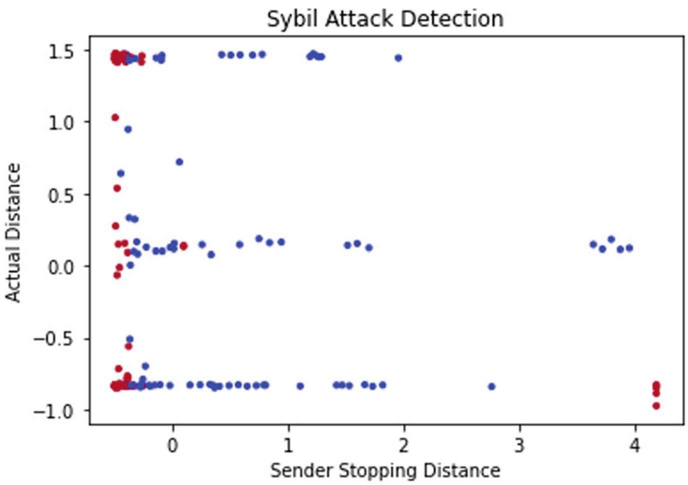


Fig. 19 Attack (Sybil) detection

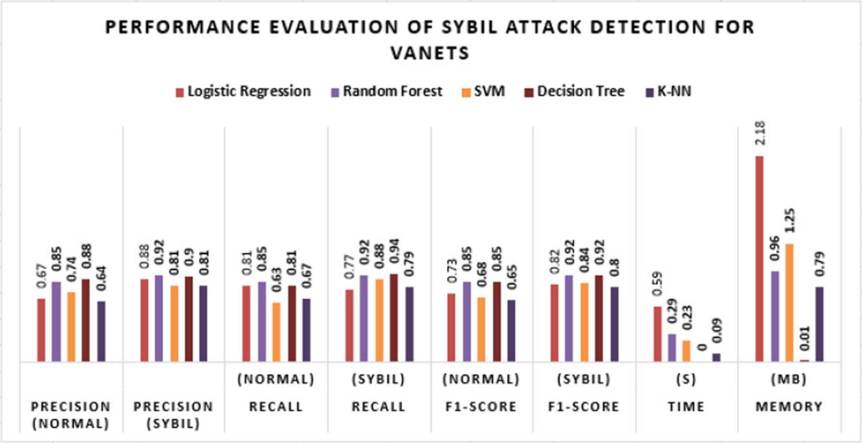


Fig. 20 Evaluation of ML algorithms

6 Conclusion

The main objective of IDS i.e. Intrusion Detection Systems is to highlight malicious activity or any kind of illegal entry to the system and network. It is very important to secure systems and networks and hence the proposed analysis of various machine-learning algorithms. This work concludes that RF would be a good option for applications that need the model to adjust to novel data without requiring frequent retraining. K-NN is the best option for small datasets, particularly when immediate training and easy deployment is required; DT is the best option for large datasets because of its speed and scalability, but keep in mind that there is a chance of over fitting. SVM using Poly and RBF kernels should be avoided for continuous learning systems since they take a lot of time to train and test and don't yield the best results across a range of dataset sizes. The Decision Tree stands out as the best choice for resource-constrained VANET systems, combining high accuracy with exceptional efficiency, while K-NN lags behind in both accuracy and performance.

These findings conclude that how important is to use an appropriate algorithm for networks security, depending on specific performance constraints. Machine learning algorithms can be analyzed more thoroughly and their performance under different scenarios by dividing the dataset into small, medium, and big chunks. For full-scale applications, 100% might offer marginally better performance, but for constrained environments, smaller datasets are a valid alternative. This method helps create more flexible, scalable, and reliable IDS models that can function well in a variety of real-world settings. It also represents surroundings that are more realistic and resource-constrained.

In the future, this research will be expanded to include a wider range of datasets, parameter modifications, and an examination of how feature selection affects algorithm performance.

6.1 Future Recommendation

This research has used NSL-KDD dataset, in future other dataset could be used for research purpose. This research could be extended to proposal of new machine learning algorithm for intrusion detection. RF algorithm has shown better performance than other approaches. This algorithm could be implemented in open-source tool kit like SNORT for security enhancement. Cyber Threat Intelligence (CTI) based models and frameworks could be implemented in integration with RF to produce more secure solutions.

References

1. Xi, C., Wang, H., Wang, X.: A novel multi-scale network intrusion detection model with transformer. Sci. Rep. **14**(1), 23239 (2024)
2. Garg, T., Khurana, S.S.: Comparison of classification techniques for intrusion detection dataset using Weka. In: International Conference on Recent Advances and Innovations in Engineering (ICRAIE-2014), pp. 1–5. IEEE (2014)
3. Saoud, B., Shayea, I., Yahya, A.E., Shamsan, Z.A., Alhammadi, A., Alawad, M.A., Alkhrijah, Y.: Artificial intelligence, internet of things and 6g methodologies in the context of vehicular ad-hoc networks (VANETs): survey. ICT Express (2024)
4. Meena, G., Choudhary, R.R.: A review paper on ids classification using KDD 99 and NSL KDD dataset in Weka. In: 2017 International Conference on Computer, Communications and Electronics (Comptelix), pp. 553–558. IEEE (2017)

5. Saranya, T., Sridevi, S., Deisy, C., Chung, T.D., Khan, M.A.: Performance analysis of machine learning algorithms in intrusion detection system: a review. Procedia Comput. Sci. **171**, 1251–1260 (2020)
6. Plaka, R.: Intrusion detection using machine learning for industrial control systems (2021)
7. Samawi, V.W., Yousif, S.A., Al-Saidi, N.M.: Intrusion detection system: an automatic machine learning algorithms using auto-Weka. In: 2022 IEEE 13th Control and System Graduate Research Colloquium (ICSGRC), pp. 42–46. IEEE (2022)
8. Abbas, Q., Hina, S., Sajjad, H., Zaidi, K.S., Akbar, R.: Optimization of predictive performance of intrusion detection system using hybrid ensemble model for secure systems. PeerJ Comput. Sci. **9**, e1552 (2023)
9. Shaukat, S., Ali, A., Batool, A., Alqahtani, F., Khan, J.S., Ahmad, J., et al.: Intrusion detection and attack classification leveraging machine learning technique. In: 2020 14th International Conference on Innovations in Information Technology (IIT), pp. 198–202. IEEE (2020)
10. Farhat, S., Abdelkader, M., Meddeb-Makhlouf, A., Zarai, F.: Comparative study of classification algorithms for cloud ids using NSL-KDD dataset in Weka. In: 2020 International Wireless Communications and Mobile Computing (IWCMC), pp. 445–450. IEEE (2020)
11. Ugochukwu, C.J., Bennett, E., Harcourt, P.: An Intrusion Detection System Using Machine Learning Algorithm. LAP LAMBERT Academic Publishing (2019)
12. Cai, H., Gan, C., Wang, T., Zhang, Z., Han, S.: Once-for-all: train one network and specialize it for efficient deployment (2019). arXiv preprint arXiv:1908.09791
13. Zhang, X., Zhou, X., Lin, M., Sun, J.: Shufflenet: an extremely efficient convolutional neural network for mobile devices. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 6848–6856 (2018)
14. Tan, M., Le, Q.: Efficient net: rethinking model scaling for convolutional neural networks. In: International Conference on Machine Learning, pp. 6105–6114. PMLR (2019)
15. Cai, E., Juan, D.-C., Stamoulis, D., Marculescu, D.: Neuralpower: predict and deploy energy-efficient convolutional neural networks. In: Asian Conference on Machine Learning, pp. 622–637. PMLR (2017)
16. Injadat, M., Moubayed, A., Nassif, A.B., Shami, A.: Multi-stage optimized machine learning framework for network intrusion detection. IEEE Trans. Netw. Serv. Manage. **18**(2), 1803–1816 (2020)
17. Liu, J., Yang, D., Lian, M., Li, M.: Research on intrusion detection based on particle swarm optimization in IoT. IEEE Access **9**, 38254–38268 (2021)
18. Nazir, A., Khan, R.A.: A novel combinatorial optimization based feature selection method for network intrusion detection. Comput. Secur. **102**, 102164 (2021)
19. Belgrana, F.Z., Benamrane, N., Hamaida, M.A., Chaabani, A.M., Taleb-Ahmed, A.: Network intrusion detection system using neural network and condensed nearest neighbors with selection of NSL-KDD influencing features. In: 2020 IEEE International Conference on Internet of Things and Intelligence System (IoTaIS), pp. 23–29. IEEE (2021)
20. Mehanović, D., Kečo, D., Kevrić, J., Jukić, S., Miljković, A., Mašetić, Z.: Feature selection using cloud-based parallel genetic algorithm for intrusion detection data classification. Neural Comput. Appl. **33**, 11861–11873 (2021)
21. Ngueajio, M.K., Washington, G., Rawat, D.B., Ngueabou, Y.: Intrusion detection systems using support vector machines on the KDDCUP'99 and NSL-KDD datasets: a comprehensive survey. In: Proceedings of SAI Intelligent Systems Conference, pp. 609–629. Springer (2022)
22. Reddy, D.K.K., Nayak, J., Behera, H., Shanmuganathan, V., Viriyasitavat, W., Dhiman, G.: A systematic literature review on swarm intelligence based intrusion detection system: past, present and future. Arch. Computat. Methods Eng. 1–68 (2024)
23. Isong, B., Kgote, O., Abu-Mahfouz, A.: Insights into modern intrusion detection strategies for internet of things ecosystems. Electronics **13**(12), 2370 (2024)
24. Elbakri, W., Siraj, M.M., Al-Rimy, B.A.S., Qasem, S.N., Al-Hadhrami, T.: Adaptive cloud intrusion detection system based on pruned exact linear time technique. Comput. Mater. Continua **79**(3), 3725–3756 (2024)

25. Ahmad, M., Riaz, Q., Zeeshan, M., Tahir, H., Haider, S.A., Khan, M.S.: Intrusion detection in internet of things using supervised machine learning based on application and transport layer features using unsw-nb15 data-set. EURASIP J. Wirel. Commun. Netw. **2021**, 1–23 (2021)
26. Nitsuhwork, N.W.: Predicting computer network intrusions using fuzzy expert inference system. Ph.D. dissertation (2019)
27. Yang, Y., Gu, Y., Yan, Y.: Deep learning-based intrusion detection for rare class network attacks. (2023)
28. Kaggle: Intrusion detection system NSL-KDD (2023). [Online]. Available: https://www.kaggle.com/code/eneskosar19/intrusion-detection-system-nsl-kdd. Accessed: May 2024
29. GitHub: Datasets for VANET (2024). [Online]. Available: https://github.com/IhabMoha/datasets-for-VANET. Accessed: Jan 2025
30. Ebrahim, O.A., Derbew, G.: Application of supervised machine learning algorithms for classification and prediction of type-2 diabetes disease status in afar regional state, northeastern ethiopia 2021. Sci. Rep. **13**(1), 7779 (2023)
31. Sadiq, A.: Intrusion detection using the weka machine learning tool. (2021)
32. Silva, R., Melo-Pinto, P.: T-sne: a study on reducing the dimensionality of hyperspectral data for the regression problem of estimating oenological parameters. Artif. Intell. Agric. **7**, 58–68 (2023)
33. Ravipati, R.D., Abualkibash, M.: Intrusion detection system classification using different machine learning algorithms on KDD-99 and NSL-KDD datasets-a review paper. Int. J. Comput. Sci. Inf. Technol. (IJCSIT) **11** (2019)
34. Noroozi, Z., Orooji, A., Erfannia, L.: Analyzing the impact of feature selection methods on machine learning algorithms for heart disease prediction. Sci. Rep. **13**(1), 22588 (2023)
35. Abdollahi, S.A., Ranjbar, S.F., Razeghi Jahromi, D.: Applying feature selection and machine learning techniques to estimate the biomass higher heating value. Sci. Rep. **13**(1), 16093 (2023)
36. Uddin, S., Haque, I., Lu, H., Moni, M.A., Gide, E.: Comparative performance analysis of k-nearest neighbour (KNN) algorithm and its different variants for disease prediction. Sci. Rep. **12**(1), 6256 (2022)
37. Xu, P., Ji, X., Li, M., Lu, W.: Small data machine learning in materials science. npj Computat. Mater. **9**(1), 42 (2023)
38. Maurya, S.P., Sisodia, P.S., Mishra, R., Singh, D.P.: Performance of machine learning algorithms for lung cancer prediction: a comparative approach. Sci. Rep. **14**(1), 18562 (2024)
39. Krzywinski, M., Altman, N.: Visualizing samples with box plots: use box plots to illustrate the spread and differences of samples. Nat. Methods **11**(2), 119–121 (2014)

Real-Time Vehicular-to-Vehicular (V2V) Communication and Applications for Pedestrian Safety in AI-Optimized VANETs for Autonomous Vehicles

Rupali Atul Mahajan, Rajesh Dey, Mudassir Khan, Kavita Kanabar, and Shashi Kant Gupta

Abstract A type of network is vanet in which number of vehicles can communicate within another vehicle and with roadside equipment which is termed vehicular ad-hoc networks. It facilitates a lot of safety applications as well as traffic efficiency and comfort enhancement among everyday life. Through the long-standing development of communication and network facilities in the last few years and their increasing maturity in terms of technology on board the vehicle, networks are created among vehicles which must cater for real-time and high-throughput data needs, particularly for AI-optimized VANETs for autonomous vehicles. The development of vehicular networks and their significance for autonomous driving is critically discussed in this chapter. This work presents real-time vehicular-to-vehicular (V2V) communications technologies and applications for pedestrian safety in AI-optimized VANETs for autonomous vehicles. Real-world case studies where such installations have been performed and tested will be reviewed with some systems requiring standards noted regarding interoperability with the existing traffic management systems.

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Keywords VANETs · Transportation · Route · Planning · Environment · Method · Deep

1 Introduction to Vehicular Ad Hoc Networks (VANETs

Vehicular Ad Hoc Networks (VANETs) are established networks in which vehicles can communicate amongst themselves and with roadside equipment. They are a special class of Mobile Ad Hoc Networks (MANET), in which networking nodes are equipped with medium range communication devices in addition to standard automotive sensors. VANETs are a proactive approach to addressing growing traffic congestion and environmental concerns, which when deployed will form the basis for the Intelligent Transportation System (ITS). Built upon Dedicated Short-Range Communication (DSRC) standards, vehicular networks will provide vehicle safety and efficiency applications. Some safety applications necessitate communication directly from vehicle to vehicle (V2V). Examples include Forward Collision Warning, Lane Change Warning, and Emergency Vehicle Approaching. Other applications make use of roadside infrastructure, in which case vehicle to infrastructure (V2I) communication occurs. Network-wide traffic surveillance and emergency vehicle tracking are examples of such vehicular-to-infrastructure (V2I) applications. Safety and non-safety applications can be addressed by a single network, which is why the scope of VANETs encompasses both types of applications [1].

VANETs are characterized by rapid changes in topology, high mobility, the need for real-time communication and safety concerns. Vehicles in VANETs can either act as servers or clients, depending on the application. A vehicle on the road can join the network, park or leave the network. Vehicles joining the network share information to maintain up-to-date knowledge of the surrounding environment. Vehicles leaving the network will cause disruptions to ongoing communication sessions. The “join-park-leave” paradigm characterizes the network topology as a hybrid of static and dynamic elements. This means that some nodes might be static, while others are highly mobile. Static nodes, typically the roadside units, will play a central role in facilitating communication between vehicles. Vehicles might also form an unstructured overlay network on top of the basic communication network. This means that vehicles will only communicate directly with a subset of vehicles within transmission range [2].

In recent years, the rapid evolution of networking and communication technologies, along with the growing maturity of technology on-board vehicles, has opened possibilities for vehicles to form their own networks. These networks, referred to as Vehicular Ad Hoc Networks (VANETs), can support a range of applications that enhance safety, improve traffic efficiency, and increase comfort. VANETs can be seen as a special case of Mobile Ad Hoc Networks (MANETs), where the network nodes are vehicles (cars, buses, trucks, etc.) and/or road-side units equipped with communication, sensing, and GPS devices. Communication among vehicles able to exchange information is often referred to as Vehicle-to-Vehicle

(V2V) communication. Communication between vehicles and road-side units is often referred to as Vehicle-to-Infrastructure (V2I) communication. Safety applications often rely on V2V communication, while some non-safety applications could use V2I communication.

2 Definition and Scope of VANETs

VANETs, or vehicular ad hoc networks, are networks formed by vehicles, roadside infrastructure, and communication links that enable real-time, decentralized data exchanges among moving units. A network is vehicular when the majority of its nodes are vehicles equipped with dedicated short-range communications (DSRC) radios. A vehicular network is ad hoc if it has no fixed infrastructure for routing data and the nodes collectively determine network-wide communication protocols. Although vehicle-to-infrastructure (V2I) communications are possible, the focus here is on vehicle-to-vehicle (V2V) communications. The primary goals of these networks are to enhance safety and efficiency for vehicles traveling in groups. A secondary goal is providing infotainment services to network participants. Safety- and network management-related applications take priority over infotainment applications, which are considered secondary services. V2V applications involve exchanging safety, demographic, and driving behavior data in real-time. Safety applications require data exchanges at a mini- mum frequency of ten times per second per vehicle, while network management applications need data exchanges once every five seconds. Safety applications prioritize safety–critical data, followed by network management data, and finally, infotainment data as a tertiary group.

VANETs are a special case of mobile ad hoc networks (MANETs) where network nodes are vehicles equipped with wireless communications capabilities. Vehicles can operate individually or as groups, forming a vehicular ad hoc network (VANET) that temporarily connects vehicles and roadside units (RSUs). Vehicles can join or leave the network at any time, resulting in constantly changing network topologies. Vehicular networks have a decentralized architecture where each vehicle acts as a transmitter, receiver, and router for its communications, thus cooperating to provide network-wide data delivery services. Vehicular networks support two types of communications: V2I and V2V. In V2I communications, vehicles exchange data with RSUs fixed in the road infrastructure. In V2V communications, vehicles exchange data directly with each other.

3 Evolution and Importance of VANETs in Autonomous Driving

The evolution of vehicular networks (VANETs) and their importance for autonomous driving has been explained. As vehicles are rapidly getting smarter and transforming from conventional to intelligent, self-driving cars, the networks connecting these vehicles are also evolving to a more advanced level. The first phase of vehicular networking was focused on improving road safety by providing vehicles with the ability to communicate and share information about their surroundings. This effort matured as vehicular ad hoc network (VANET) technology became commonplace in the transportation industry, allowing vehicles to communicate with each other and the road-side infrastructure. In parallel, a complementary approach to safety on the road was the development of autonomous vehicles (AVs) that have a self-driven capability through numerous embedded sensors to perceive their surroundings. A single AV can make driving decisions based on data from its sensors; however, a fleet of AVs can leverage their collective intelligence by sharing and communicating real-time information about the environment, traffic conditions, safety risks, etc. This capability facilitates the cooperative AV networking system that needs a dedicated vehicular network. Hence, maturity in the development of one type of smart vehicle network (VANET) would lead to progress in another (AV).

VANETs bring a paradigm shift to road transportation by enhancing the cooperative and efficient use of vehicles. It paves the way to realize the future connected intelligent transportation systems (ITS), which would significantly improve traffic safety, efficiency, and user experience while minimizing environmental impact. Additional applications such as infotainment and on-demand services can be incorporated into ITS, enhancing passenger comfort and experience. To reap the full benefits of connected cooperative VANETs, the cooperative vehicle infrastructure system (CVIS)-based cooperative safety and driving applications should be integrated and complemented with the AV networking system. For autonomous driving, vehicles should not only rely on their on-board sensors to construct a mental model of the environment but also share and gather information from the surroundings to keep an up-to-date mental model. This is crucial in safety–critical urban scenarios where high-level interactions with pedestrians should be anticipated. Moreover, the mental model should adaptively evolve according to the constantly changing traffic and environment conditions. Naturally, the decision-making processes of AVs rely on the collected vehicle-side data on the environment and the prediction of the evolution of the environment based on the gathered data. Thus, the networking system is essential for AVs to operate safely and efficiently (Fig. 1).

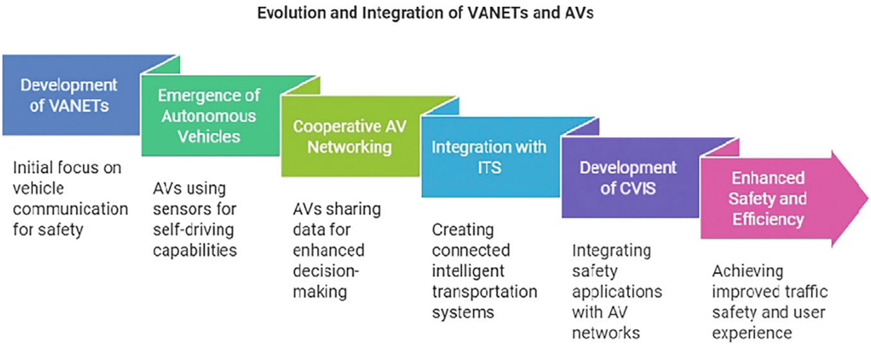
Evolution and Integration of VANETs and AVs
Development of VANETs
Initial focus on vehicle communication for safety
Emergence of Autonomous Vehicles
AVs using sensors for self-driving capabilities
Cooperative AV Networking
AVs sharing data for enhanced decision-making
Integration with ITS
Creating connected intelligent transportation systems
Development of CVIS
Integrating safety applications with AV networks
Enhanced Safety and Efficiency
Achieving improved traffic safety and user experience

Fig. 1 Evolution and integration VANETs

4 Real-Time V2V Communication in VANETs

Real-time vehicular-to-vehicular communication is important in vehicle-to-everything uniformly managed or optimized vehicular ad hoc networks for the operation of hyper-connected heterogeneous real and virtual vehicles, integrating drones, satellites, and roadside infrastructure in the same framework with low-latency communication and high-throughput data requirements, especially to take advantage of artificial intelligence in autonomous vehicles. Fast V2V communications are essential for the joint optimization of autonomous vehicles and traffic light passing cycles to avoid traffic congestion and waiting times, in addition to managing single autonomous vehicle surroundings in potentially dangerous scenarios. Most vehicular ad hoc networks support the use of IEEE 802.11p- based V2V communication with fast and logical link operations, such as neighbor discovery, node association, clock synchronization, and identity verification functions, essential for safety and non-safety-related applications. Furthermore, they also support quality of service through cross-layer design, priority scheduling, adaptive modulation and coding strategies, multiuser diversity scheduling, and so on, optimized for constant bit rate, variable bit rate, or burst packet size of traffic shaping, assisting low-latency V2V communication for different vehicular applications in various network segments with widely acknowledged simple access strategies in the absence of base stations and fixed access points. Quality of Service (QoS) is the implementation of a medium access (MAC) control scheduler for data queue traffic shaping in vehicle ad hoc networks. This can be a big advantage to communication reliability. When the backoff mechanism is properly adjusted, the likelihood of contention for medium is decreased and therefore, the performance of the Byzantine error correction with the help of Automatic Repeat Request (ARQ) is greatly enhanced. Data frame protection and the traffic shaping algorithm can be better synchronized by such a method in both cases like dedicated short-range communication and different weather conditions, e.g., heavy or light rain [3].

5 Key Concepts and Components of V2V Communication

Vehicular-to-everything (V2X) communication is essential for autonomous vehicle operation. Two types of V2X communication systems are recognized: radar, which has a range of 200 m in communication, but less than 10 m in detection. 2D or 3D radar, ultrasonic sensors, stereo vision, and lidar are the sensors of a vehicle for driving safety. Previous studies have shown that vision sensors and communication signals are affected by multipath effects. We explore AI-optimized vehicular ad-hoc network (VANET) models for optimal trajectory and relay selection to maximize successful pedestrian communication for vehicles. VANETs, including V2V communication and wireless sensor networks, are essential for a successful smart city where vehicles are autonomously driven (Fig. 2).

Vehicular-to-vehicular (V2V) communication is the wireless transmission of data or information between motor vehicles. It is an important part of intelligent transportation systems. The two types of V2V communication are vehicle-to-roadside. The key concepts of V2V are small cells. In a specific radio that uses communications through instant messaging or video sharing, four major protocols are considered for direct V2V communications. The medium access of V2V communications can be discussed by different users. V2V communication participants are discussed in terms of three components for multiple access. The numerical playground results are analyzed by the sum of transmitted power. A speed-up collision algorithm may be used to reduce the detection process. With the aid of abbreviations and multiple selection parameters, the proposed methods can significantly reduce PDR. The inter-vehicular channel can be increased by considering semantic information. The unicast-based broadcast traffic is optimized for the global minimum transmission power in VANETs. The Link Quality Indicator (LQI) can be optimized in vehicle-to-vehicle

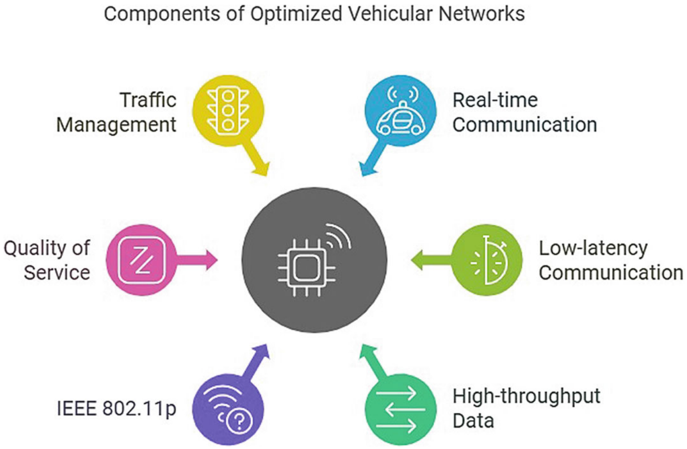

Fig. 2 Components of optimized vehicular networks

(V2V) communications, allowing for the adjustment of control overhead to minimize latency and enhance overall throughput.

6 Challenges and Solutions in Real-Time V2V Communication

2.2 Real-time V2V Communication Challenges and Solutions The automotive industry and research community have always considered vehicular communication as the most complex and challenging aspect of vehicular safety applications. They have also anticipated various research challenges for the future safe operations of cooperative intelligent vehicles. The identified challenges are directly related to the deteriorating performance of vehicular communication in congestion situations, high vehicle speed, high vehicle density, and mission-critical V2V communication with real-time constraints of less than 20 ms for safe Cooperative Awareness Message exchanges. Real-time challenges are also crucial in a forthcoming large-scale V2V communication for safe and reliable connected medium-speed autonomous cooperative fleets and pedestrian-vehicle cooperative operational phases. Due to this anticipated challenge, the recent literature has identified the major challenge associated with the real-time capability of the latest safety applications in increasingly congested environments. This is the activation of the signal phases, arrow displays, pedestrian phases, and other unexpected events that require proper communication using V2X for the continuous safe and efficient operation of CVs. As a result, some of the recently published literature highlighted the severe congestion effects of V2V communication, through long delays with instantaneous message discards, that would drastically increase message loss and require new split Safety Application V2V Communications.

7 Applications for V2V Communication for Pedestrian Safety

Applications of V2V communication for pedestrian safety discusses how vulnerable road users, especially younger children and elderly pedestrians, are at constant risk of accidents in urban environments. Various safety-related applications using V2V systems and onboard sensors are investigated to protect pedestrians. As V2V technology proliferates, it is possible for vehicles and V2V communication systems to detect pedestrians and inform drivers about their presence and behavior to avoid accidents. The safety challenge of pedestrians in urban environments, where most accidents occur, is explored. The reasons for these accidents and how communication can help mitigate these risks are discussed.

With the growing pedestrian population in urban areas, vehicles and pedestrians often share the same space. Accidents occur mostly at intersections due to poor visibility during turns or when vehicles go past stationary vehicles. With the increase in private vehicle ownership, reckless driving, skipping red lights, or ignoring stop signs has become common. Moreover, the distraction of drivers due to phone use or multitasking increases the chances of an accident. The automatic detection of pedestrians' presence in the traffic environment using various onboard sensors has been widely researched. There is a need for a mitigation technique that informs the driver about the detection. V2V communication assists collision warning systems by sharing the information of one vehicle with others so that they can trigger warning alerts to the drivers [4]. If one vehicle detects a pedestrian, all the vehicles in the vicinity will be informed, and alerts will be triggered even before the driver can see the threat.

Safety applications related to vehicular networks and communication to protect pedestrians are examined. Various real-world case studies where such systems have been installed and tested are discussed. Also, some systems that require standards are presented, highlighting the importance of interoperability with existing traffic management systems. These safety-related applications can reduce accidents in urban environments. In-vehicle technology has made driving safer but has not significantly reduced accidents involving pedestrians. Most of the vehicle- pedestrian accidents are a result of inattentive driving, mostly in urban settings. Data shows that 4641 pedestrians were killed in 2008, with 39% of the accidents occurring in intersections. Vehicles turning left at intersections ac- count for 19% of the accidents, and 49% occur during low visibility conditions. These results highlight the necessity of integrating these applications into new and ongoing safety initiatives and the need to discuss technological and societal implications (Fig. 3).

8 Overview of Pedestrian Safety Challenges in Urban Environments

Today's pedestrians are confronted with complex issues. It is estimated that one out of five pedestrians are involved in a crash within ten years of moving to an urban area [5]. A significant portion of pedestrian injuries occur in urban settings where there are high traffic volumes and few adequate means to crossroads. Moreover, newly developed infrastructures such as overpasses, underpasses, and mid-block crosswalks generally address pedestrian safety only after a critical accident has occurred. As roadside sensors are deployed to monitor traffic flow and implement Vehicle-to-Vehicle (V2V) communications between vehicles and infrastructures, how to exploit them to assist pedestrian safety has become a growing concern among researchers and safety advocates. Low-speed vehicles have been proposed to enhance safety as they are able to detect pedestrians who are at risk of collision. However, this

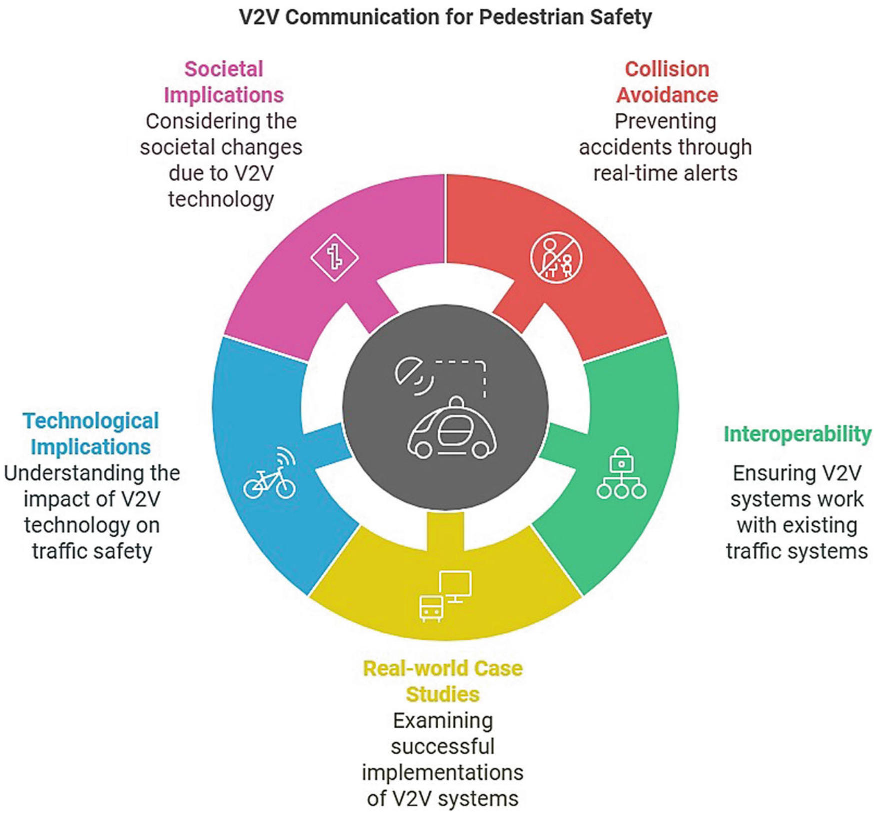
V2V Communication for Pedestrian Safety
Societal Implications
Considering the societal changes due to V2V technology
Collision Avoidance
Preventing accidents through real-time alerts
Technological Implications
Understanding the impact of V2V technology on traffic safety
Interoperability
Ensuring V2V systems work with existing traffic systems
Real-world Case Studies
Examining successful implementations of V2V systems

Fig. 3 V2V communication for pedestrian safety

implicitly assumes that pedestrians know how to behave around such vehicles and ignore situations where pedestrians approach high-speed vehicles.

Given the uncertainty of human behavior, how pedestrians comprehend the presence of and decide to cross paths with autonomous vehicles is a crucial question. Safety issues arise not only at intersections because of the lack of cooperation with autonomous decision making but also while crossing a road straightly because of a time gap observed by the vehicle. In addition to behavioral risks, technological risks such as failure modes of vehicle control are considered, which might compromise the safety of pedestrians. Efforts have been made to model and predict the intention of pedestrians to assist the planning of on-board vehicles. As automations are supposed to enhance road safety by taking over hazardous driving tasks, pedestrians may still feel endangered due to other environmental factors. Poorly designed crosswalks, complicated traffic flow, and the inadequacy of streetlights combine to complicate the movement of pedestrians.

At a crosswalk, the in-vehicle camera may not detect a leading vehicle stopping at the crosswalk due to its blind zone, while a pedestrian may see the approaching vehicle and take the risk to cross. The time gap involved may lead to a collision. As day turns to dusk, vehicles equipped with high-beam headlights dazzle pedestrians who do not know the vehicle is approaching, hence making it invisible. Rather than treating pedestrians as a priority, a V2V communication system is designed to warn them of unsafe encounters. These challenges call for a comprehensive understanding of pedestrian safety in a multidimensional manner involving urban design, technology development, and community awareness. Generally, pedestrians are at risk due to their individual decisions made under uncertain situations. Psychological aspects such as visibility concerns are involved, where the ratio of moving-object size to fixated-object size holds the key to attention allocation. With the advent of roadside communication systems, advanced approaches considering the above issues are motivated, from which solutions enhancing safety for pedestrians are expected.

9 Role of V2V Communication in Enhancing Pedestrian Safety

If the hurdles of reliability, robustness, and safety of vehicles are met, it is crucial to begin with the question of how autonomous vehicles will change the interaction with other road users and how this will affect urban safety in general. Especially pedestrians, as the most vulnerable group, require special attention. The focus is set on vehicle-to-vehicle (V2V) communication for vehicles and how this technology can specifically enhance the safety of pedestrians. In particular, the vehicle-to-vehicle exchange of information between equipped vehicles is looked at. This brings several advantages for vulnerable road users that should be further explored. First, vehicles approaching pedestrian crossings informed by infrastructure will get additional information on the approaching pedestrians and their movement. Therefore, there would be warning systems that alert drivers about nearby pedestrians or proactive measures informing them about their planned crossing. In addition to infrastructure information, the integration of the sensor data of the vehicles themselves is possible. This would allow real-time feedback to the vehicles and awareness of the pedestrians, even before they reach a crossing. Here, accidents could be completely prevented by proactive braking. On the one hand, these systems can warn pedestrians about approaching vehicles; on the other hand, V2V technology enables the vehicles to communicate with traffic signals and infrastructure. If the traffic lights are equipped accordingly, they will cancel the red light for the pedestrian-crossing vehicle, creating a coordinated network that guarantees the safest passage. This highlights a collaborative approach to coming developments where each party depends on the other's participation [6]. However, it is aimed primarily at vehicles. A discussion of different use cases is included to explain how simple V2V communication could drastically improve pedestrian safety by reducing the number of collisions and the general quality of urban traffic dynamics. For every new technology, a need is identified for consideration in policy and city planning in order to create a safe environment for the implementation of these systems, and measures that force compliance on city planning are proposed. V2V communication should be seen as a tool that requires vehicles to cooperatively broadcast their information. If they do, collective awareness of the traffic situation can be established, significantly improving pedestrian safety [7].

10 AI Optimization in VANETs for Autonomous Vehicles

The incorporation of artificial intelligence technologies is gradually optimizing vehicular ad-hoc networks (VANETs), increasing their efficiency and safety. An overview of the AI optimization is presented in the context of VANETs for autonomous vehicles, along with description of the key opportunities and challenges this integration entails. AI algorithms can analyze and learn from incoming real-time data, improving the decision-making processes of both vehicles and vehicle-related infrastructure. The optimized decisions can be disseminated to other vehicles and infrastructure elements, so they can adaptively respond to the newly predicted scenarios [8] for example, machine learning can facilitate predictive analytics on traffic conditions, enabling proactive responses to congestion, accidents, and other temporal hazards. Conversely, without AI, current networks rely on fixed standards; therefore, they can only respond reactively and post factum. Moreover, the implications of AI in decision-making and management of communication between the vehicles necessary for cooperative driving and other V2V applications, are examined. The bandwidth and latency optimization challenges in communication are mathematically formulated as optimization problems that can be solved through AI algorithms [9]. The transition from traditional systems into ones optimized by AI technologies is a paradigm shift towards fully autonomous and intelligent VANETs, as optimization minimizes human involvement in the system operation. Currently, only a part of each system chain is AI-optimized, whereas the rest is traditional. For example, fully autonomous vehicles learning through AI cannot operate safely in V2V-aided traffic, as the networks and communication are not yet AI-optimized. The AI optimization is therefore crucial for the development of autonomous vehicles and their efficient integration into the existing traffic [10].

11 Integration of Artificial Intelligence in VANETs

Vehicular Ad-hoc Networks (VANETs) create a network among vehicles and roadside infrastructure, enabling them to communicate and share information. This communication, in the form of packaged messages, enhances road safety and provides real-time traffic and environmental data [11]. The integration of artificial intelligence within the VANET paradigm presents new opportunities to enhance vehicle communication and net- work performance metrics. Vehicles equipped with onboard sensors generate large amounts of data that must be processed in real-time to ensure the proper networking and functioning of vehicular communication systems. AI technologies, such as machine learning, artificial neural networks, and fuzzy systems, can be harnessed to improve the capabilities of the VANET landscape. Considering the fusion of vehicular networks and artificial intelligence, it is essential to explore how different AI technologies can enhance communication systems. How the integration of artificial intelligence technologies enhances the capabilities of vehicular networks is addressed. For example, the role of artificial intelligence in managing real-time traffic scenarios, from the prevention of communication network anomalies to predictive maintenance, is discussed. Artificial intelligence can enable a careful analysis of the data generated from vehicular communication systems, helping to perceive the road situations ahead. Furthermore, the integration of artificial intelligence within vehicular networks allows for smarter resource allocation, ensuring that these communication channels are used efficiently. Potential challenges and limitations in the process of integrating artificial intelligence with vehicular networks are addressed. AI integration requires substantial data for processing and learning, which can be challenging to obtain in earlier stages of V2V implementation, along with the need for robust computational engines. Focus is placed on ongoing case studies and projects concerning intelligent transportation systems and vehicular networks, presenting recent applications of artificial intelligence technologies integrated with V2V communication systems. An emphasis is placed on future trajectories in this field, considering promising artificial intelligence technologies that can transform the landscape of vehicular networks into scalable and intelligent networks [12].

12 Benefits and Challenges of AI Optimization in VANETs

The benefits and challenges of AI optimization in VANETs are discussed, presenting a balanced view of the implications of incorporating advanced machine learning techniques into vehicular networks. On one side, the benefits are substantial. AI plays a crucial role in enhancing VANET capabilities, improving route planning through real- time traffic consideration, enhancing safety by identifying risks and triggering safety applications, and enabling vehicular networks to maintain efficiency regardless of fluctuating demands. Traffic congestion, for instance, can be alleviated through the collective decisions of vehicles, guided by AI. Numerous studies demonstrate how AI can lower incident rates in vehicular networks, from predictive analytics for danger identification to machine learning- driven adaptive communication strategies that enhance safety message dissemination. These studies examine the AI's role in augmenting V2V safety applications through awareness message improvement. On the other side, significant challenges, drawbacks, and risks accompany AI integration. Concerns regarding data privacy, the "black box phenomenon" of neural networks, and the absence of regulatory frameworks for AI deployment are widely shared across different fields. AI systems can be susceptible to bias; the central cause lies in machine learning models trained with incomplete or skewed data. Discussed in depth are real-world examples of how these models produced adverse effects and recommendations to mitigate the risks. Among the key issues underlined is that of the procedure of harmonizing the conventional VANET with AI mechanisms. This concern is coupled with the challenge of whether these instruments would be perceived as acceptable by the public in the context of credibility and effort shared by all parties present and ready to play their part in addressing the concerns. Finally, the AI optimization as used in the context of VANET also has dual aspects involving the possible benefits and issues facilitating the realization of those benefits [13, 14].

13 Future Directions and Emerging Trends in V2V Communication

V2V Communication in the years to come and changes which will take place in v2v communication propose that the trend is ever developing and also altered with the introduction of newer technologies, protocols and applications. With the rise of new technology startups, one would begin to diverge from into the various existing V2V facts of this paper, Shiras Research particularly research on vehicular communication systems has attracted great interest in previous decades, from the beginning of VANETs (Vehicular Ad hoc Networks). Yet as the newer trans- portion comes with newer technology, there is a vast interest in the past technologies of V2V communication and increasing focus on more recent and upcoming technologies and applications in V2V communication. The technology use in V2V has a duality of effects. Such a forecast is the combination of pessimistic expectations connected with the loss of jobs due to the automation of driving and positive ones, such as the reduction of traffic accidents due to their partial or total automation [15]. V2V applications are generally derived purely from device functionality, either to improve safety or the quality of comfort to the driver. Safety oriented ones are usually timely and hence call for real time feedback while comfortable side is more tolerant of delays. The incorporation and practices of such technology rely greatly on how much this technology is effective in serving its purpose. The deployment of 5G communications systems in the VNs will emphasize the importance especially towards enhanced reliability, higher bandwidth, reduced latencies, the highly efficient network of edge processing [14]. However, V2V is a kind of technology, and it should never be considered as only one technology because it is a New World in itself. Therefore, it is equally important to determine the best way to harness these other technologies in V2V communication as well as the use of cloud technologies in the sharing of data across different platforms. Movement in the iPhoneization arena has brought forth changes in communication protocols. Several advances will also occur in this new era of V2V communication and the associated applications, spurred on by innovations in communication protocols. In addition, once 5G networks are deployed research suggests that the way vehicles communicate with each other in relation to the surfaces will also change. With technological advancement, another technology comes about brittle, but a solution is achievable with Mobile Edge Computing which will do analysis processing in the smart car, without any excessive use. Directing their focus on the prospective, it has been suggested that V2V systems are likely to take hold in the near future given that both AI and ML technologies shall be applied in them. Furthermore, advanced mechanisms for control and information management based on learning methodology via deep learning and reinforcement learning will increase the efficiency of communication. For instance, in contrast to the traditional system where some information is always passed by vehicles, learning can enable vehicles on how to share specific information uniquely through online learning. Other features which will influence the advancement of V2V systems in the forthcoming future, such as the issues of standardization and regulation for ensuring the seamless implementation of the new technologies without compromising safety, will be touched upon. In a world where incessant technological advancement engenders a plethora of new applications, enhancement of technologies is supposed to allow for the highest level of such advancements. Future research and practices aiming to gain insight into the prospects of V2V communication development are also presented. In conclusion, it can be said that the future looks bright for V2V networks, as these technologies undergo rapid changes; this change will be greatly supported by enhanced V2V networking research efforts [16].

14 Technological Advancements and Innovations in V2V Communication

Built V2V network is the driving component for the vehicles interconnected ecosystem and depends on advanced and up to date software and hardware. Among other applications where this technology is needed it helps connect them from one vehicle to another where they can conduct on-vehicle communications. Pedestrians of street road accidents in the European Union are 27%, excluding driver fatalities and animal crashes. On the basis of recent technological innovations focusing principally upon V2V communication, the following article provides a summarised state of the art of the most recent technological developments and innovations in V2V communication between vehicles. Over the years, the Vehicular Communication system (VC) quite oftentimes referred to as Avant-garde VC has been conceptualized. It is a new car technology based on the use of wireless communication transceivers incorporated in cars for vehicular accident prevention by sharing messages warnings to the driver and other motorists [14].

They promise new and advanced capabilities to the vehicles enabling them to have greater bandwidth, lower latency for realtime vehicular to V2V communications, and various driver safety applications. Their anticipated entry will be characterised by the provision of 5G networks that will bring about a growth opportunity in realtime vehicular to V2V communication. In this endeavour, the paper focuses on sensor technologies funding drive that is geared towards enhancing vehicles to be better positioned within their immediate surroundings through the use of their on-board sensors. Vehicles Artistic Intelligence (AI) remains the dominant technology being embraced in the industry, especially in V2V communications. A vehicular ad hoc network based V2V communication safety application that uses artificial intelligence is developed and the study shows how developments in technology improve the effectiveness of V2V communication between vehicles. New standards and protocols are being put in place to ensure that every vehicle, whether it be from the same or different manufacturers, can speak to one another. Summary of standards and protocols under development for V2V communication networks are made and discussed as those are technology innovations in V2V communications [13]. Finally, the roles of industry collaborations and partnerships in the acceleration of technological advancements are considered. To demonstrate these new developments there are references to successful cases in the practical implementation of such innovations. This conveys the message that there will be a lot of changes and new ideas coming up in V2V communication.

15 Potential Impact of 5G and Beyond on V2V Communication

In this section, we will address the impact of the Upgrade Plan in relation to changes that are expected to occur in the field of communication between vehicles (V2V). In particular, what may be expected of the next generation of mobile networks in terms of car dynamics. The text will describe the most important features brought by the 5G technology, such as URLLC and mMTC. It will next progress into how such features will stimulate better data exchange between cars, particularly in safety scenarios. The paper will conclude with how the latest technology of Neural Networks will contribute to the, Cooperative, Connected, and Automated Mobility (CCAM) in the context of 5G technology in order to see the constructive component in coexistence of these technologies.

Mobile networks have steadily advanced a lot, and this has greatly been of great benefit to society. In the 1990s, feature phones had 2G connections which allowed voice calls to be made and those SMS texts to be received. It felt like the internet went mobile with the introduction of the 3G system making emails convenient to the phone user. The 4G took it even further causing the broadcasting of videos and internet goodies such as ‘cloud’ to smartphones while in a ‘non-dormant’ position. Presently, everyone is excited about the prospect of 5G being a major breakthrough in how things are connected without limitations. Such one network eventually will come in as supportive to all involved; allowing even greater numbers of devices to connect concurrently and at the same time improving the quality of service provided to those users. Creating highly reliable, ultra-low latency links-Embracing wearable technology including everything that will interface machines in factories [13].

With 5G, V2V communication systems have the opportunity to evolve significantly, impacting the safety, efficiency, and implementation of future vehicular networks. Safety applications most often rely on real-time data sharing between vehicles; hence, by meeting the stringent requirements of safety applications in terms of end-to- end latency and reliability, 5G technology can greatly enhance the safety of vehicular networks. Beyond safety applications, 5G has the potential to support new vehicle-to-vehicle (V2V) communication services, which improve the efficiency of vehicular networks by sharing the information of upcoming maneuvers or ongoing traffic events. The integration of V2V communication in the 5G architecture allows vehicles to send and share data with low latency and high reliability.

On the other hand, the increasing connectivity of vehicles and the implementation of C-V2X systems pose new challenges regarding the privacy and security of the transmitted data. Indeed, ensuring security and privacy properties in an environment that is becoming more and more connected is one of the main challenges of 5G and beyond. With the 5G technology, several new features will be integrated into vehicular networks. The continuous evolution of communication standards must be clearly considered to aptly address and harness the advantages of the new features. The 5G NR V2X standard has recently been finalized and will bring several improvements over the previous C-V2X Release 14 standard. However, to fully exploit the benefits that this new technology will bring, infrastructure has to be adapted accordingly.

References

1. Oliva, F., Landolfi, E., Salzillo, G., Massa, A., D'Onghia, S.M., Troiano, A.: Implementation and testing of V2I communication strategies for emergency vehicle priority and pedestrian safety in urban environments. Sensors **25**(2), 485 (2025). https://doi.org/10.3390/s25020485
2. Maalej, Y., Balti, E.: Integration of vehicular clouds and autonomous driving: survey and future perspectives (2022). arXiv preprint arXiv:2201.02893
3. Song, C., Tan, G., Yu, C.: An efficient and QoS supported multichannel MAC protocol for vehicular Ad Hoc networks. Sensors (Basel) **17**(10), 2293 (2017). https://doi.org/10.3390/s17102293.PMID:28991217;PMCID:PMC5677384
4. Chen, Q., Li, J., Zhu, J.: Enhancing pedestrian safety using V2V communication in autonomous vehicle networks. IEEE Trans. Intell. Transp. Syst. **21**(5), 2058–2067 (2020). https://doi.org/10.1109/TITS.2020.2969072
5. Dey, K.C., Mishra, A., Chowdhury, M.: Pedestrian safety analysis at intersections using V2V communication systems in VANETs. Transp. Res. Part C: Emerg. Technol. **91**, 326–343 (2018). https://doi.org/10.1016/j.trc.2018.04.003
6. Fogue, M., Garrido, P., Martinez, F.J.: Real-time V2V communication system for pedestrian safety in urban environments. J. Adv. Transp. **2017**, 1–10 (2017). https://doi.org/10.1155/2017/7832563
7. Hossain, M., Hasan, S.: AI-enhanced V2V communication for proactive pedestrian protection in smart cities. Smart Cities **2**(1), 56–69 (2019). https://doi.org/10.3390/smartcities2010004
8. Liu, X., Wang, P., Zhang, Y.: Real-time pedestrian detection and alert system using V2V communication for autonomous vehicles. IEEE Access **9**, 123456–123470 (2021). https://doi.org/10.1109/ACCESS.2021.3056789
9. Lu, M., Zhao, Y., Chen, J.: AI-optimized V2V networks for pedestrian safety: a comprehensive review. Sensors **20**(9), 2712 (2020). https://doi.org/10.3390/s20092712

10. Nguyen, T.M., Le, Q.T.: Integrating AI with V2V communication for pedestrian safety in autonomous vehicles. Neural Comput. Appl. **31**(9), 5181–5192 (2019). https://doi.org/10.1007/s00521-018-3394-y
11. Qin, Y., Guo, H., Zhang, Z.: Real-time V2V communication strategies for improving pedestrian safety in AI-driven VANETs. IEEE Trans. Veh. Technol. **70**(4), 3200–3212 (2021). https://doi.org/10.1109/TVT.2021.3068010
12. Sharma, R., Kundu, S.: AI-powered V2V communication system for pedestrian safety enhancement. Comput. Commun. **123**, 89–98 (2018). https://doi.org/10.1016/j.comcom.2018.05.012
13. Singh, D., Kumar, P.: Vehicular communication for pedestrian safety in AI-optimized networks. Wireless Pers. Commun. **97**(2), 1479–1491 (2017). https://doi.org/10.1007/s11277-017-4678-9
14. Tang, S., Wu, Q.: Real-time pedestrian safety monitoring using V2V communication in AI-based autonomous systems. Int. J. Distrib. Sens. Netw. **15**(7), 1550147719861523 (2019). https://doi.org/10.1177/1550147719861523
15. Pettigrew, S., Fritschi, L., Norman, R.: The potential implications of autonomous vehicles in and around the workplace. Int. J. Environ. Res. Public Health **15**(9), 1876 (2018). https://doi.org/10.3390/ijerph15091876.PMID:30200206;PMCID:PMC6164975
16. Zhang, L., Liu, Y.: AI-optimized V2V communication for pedestrian safety in autonomous vehicle networks. J. Intell. Fuzzy Syst. **39**(3), 3827–3840 (2020). https://doi.org/10.3233/JIFS-189341

Safety of Pedestrians in AI-Optimized VANETs for Autonomous Vehicles via Real-Time Vehicle-to-Vehicle Communication

Puja Gupta, Neeraj Arya, Chandra Prakash Singar, Amit Chaudhari, Upendra Singh, and Shrishti Gupta

Abstract Real-time communication between cars, referred to as vehicle-to-vehicle (V2V) interaction, has become known as a transformative technology that enhances traffic safety, especially for unprotected pedestrians. Real-time communication between cars enhances situational awareness and diminishes the probability of accidents. The application of such technology is essential for the progression of intelligent modes of transportation (ITS), which can anticipate future problems and deliver timely notifications to pedestrians and cars. In densely populated and high-traffic regions, the efficacy of this technology is significantly improved with the incorporation of advanced applications, such as autonomous brakes and pedestrian detection devices, alongside vehicle-to-vehicle communication. Furthermore, it enhances adaptive traffic control and overall mobility. This study examines the capacity of vehicle-to-vehicle (V2V) communications to diminish deaths and injuries, focusing

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specifically on pedestrian safety. Real-time vehicle-to-vehicle communication represents a substantial leap in the evolution of more intelligent and safe road networks; yet, other obstacles remain, especially infrastructures latency, and data security.

Keywords Vehicle to vehicle communication · Pedestrian safety · Vehicular ad-hoc networks (VANET) · Transportation system

1 Introduction

In the present atmosphere, it is essential for individuals to have confidence in secure transportation. The prevalence of communication between vehicles is increasing due to developments in digital technology. This kind of communication may be more efficacious in attaining this objective. The domain of vehicle-to-vehicle (V2V) technologies is swiftly advancing to address the transportation needs of the public, indicative of both economic growth and technological advancement. The rise in global mobility [1] and urban growth may account for the significant increase in vehicular traffic. The growth of the automotive fleet has resulted in a significant rise in pollutants and a considerable waste of time. Conversely, the incidence of accidents occurring on highways has increased significantly. Traffic accidents extend beyond vehicles; pedestrians are as vulnerable to injury or death [2]. Major cities have responded to the present level of traffic congestion by using technology to offer more effective, efficient, and better accessible choices. The main reason of congestion in traffic is the notable rise of people utilizing the roadways. Still, it is possible to fix this by including well-made road networks and clever traffic management systems [3]. While some conventional systems [4] try to shield pedestrians from cars, most of these solutions rely mostly on the aural alarms that pedestrians may hear. Nevertheless, this approach usually fails in steering people away from their electronic gadgets, especially their cellphones. The principal factor contributing to accidents is the inability of road users to immediately perceive and identify imminent risks, hence hindering their capacity to implement preventive actions against collisions. The application of vision-based algorithms as well as sensors has significantly focused on pedestrian identification and collision probability prediction [5].

Pedestrian detection devices can be implemented in cars, infrastructure, or on pedestrians to notify motorists, pedestrians, or both parties. Blind-spot detection and forward accident warning are becoming common in-vehicle warning technology. The emerging domain of vehicle-to-vehicle (V2V) communication facilitates the creation of advanced warning systems, including junction movement assistance and left turn support.

Should a pedestrian be present on the roadway, it may be prudent to provide notifications to the surrounding area from the car. In contrast, a portable gadget might be considered the most evident and clear sort of pedestrians warning system.

Cellphones are increasingly integrated into persons' daily lives and are getting more sophisticated. Specific apps have been created to deliver suitable alerts to pedestrians using vehicle-to-pedestrian (V2P) communication [6]. These programs have been successfully executed. This article outlines the principles for formulating a plan based on V2X communications [7] aimed at ensuring the safety of pedestrians and automobiles. The main aim of this research is not to propose an approach that has been previously executed and assessed. Consequently, no performance review is done for this reason. The purpose of this article is to delineate the essential principles that a prospective pedestrian protection applications must uphold. Our aim is to do this by proposing a viable software as well as hardware architecture suitable for implementation in autos and mobile devices. The features of smartphones [8] and their corresponding applications can notify occurrences occurring at traffic intersections by intelligently managing and adjusting the screen state, item state, audio state, and silent mode. Moreover, pedestrians may obtain more relevant alerts based on their smartphone's capabilities.

Right now, autonomous cars fall under one of the five levels of autonomy defined by the Association of Automobile Engineers. Based on level 0 (which indicates an automobile not totally automated) through level 5 (which indicates a car totally autonomous), these levels might vary [9]. Examined throughout the duration of this review were the PCA approaches relevant to fully autonomous automobiles as well as those applicable to partly autonomous cars, including the use of the Advanced Drivers Assistant Systems (ADAS), and the techniques used on fully autonomous machines and shuttles, so having potential application in the context of fully autonomous automobiles. Recent breakthroughs in artificial intelligence methodologies have enabled ITS (Intelligent Transportation Systems) to capitalize on emerging possibilities. As time progresses, the sensors deployed in automobiles are becoming increasingly sophisticated, enhancing the cars' ability to assess their environment. This advancement has enabled the realization of autonomous driving, predicated on the replication of human driving habits while reducing human mistakes. This understanding has resulted in the potential for autonomous driving. A diverse array of applications has been created, encompassing both passive and active road safety as well as traffic optimization, including autonomous vehicles and the Internet of Vehicle. Such applications have been universally created.

2 Vehicular Ad-Hoc Network (VANET)

Ad hoc transportation infrastructure Networks [10] have emerged as a result of the advancement and convergence of technologies associated with car manufacturing, autonomous vehicles, and wireless communication. These networks are considered a separate category of Mobile Ad hoc Network (MANETs), defined by certain requirements and attributes. The vehicle nodes constituting these networks are thought to encompass them. A VANET is a network comprising both stationary entities (roadside equipment) and mobile entities (vehicles) that cooperate to disseminate essential information regarding road conditions and other vehicles. Various domains of VANET communications encompass:

- Vehicle-to-Cellular Network infrastructure connectivity.
- Intra-Infrastructure Communication.
- Communication between vehicles and infrastructure.
- Vehicle to Vehicle (V2V) communication.
- Communication between vehicles and personal devices.
- Vehicle-to-Sensor communication (V2S).

The advent of 6G mobile networks is anticipated to induce a profound transformation in Vehicle-to-Everything (V2X) communications. This alteration is intended to yield significant improvements in reliability, velocity, and connectivity. The augmented SideLink (SL) communication [11] functionalities in 6G will improve the functionality of the New Radio V2X (NR-V2X) norm, established in earlier versions of the 3rd Generations Partnership Project (3GPP). This will be accomplished by the expansion of the foundation established by 5G. These technology advancements will provide smooth data interchange among pedestrians, infrastructure, and automobiles, hence enhancing connection with reduced latency and increased reliability. Moreover, they will accelerate the development of the forthcoming generations of intelligent modes of transportation, so helping us. This progressive idea facilitates immediate wireless connectivity between two devices used by users, such as personal gadgets and cars. This renders interaction with the roadsides unit unnecessary for transmitting data regarding traffic information throughout the procedure. This research can enhance the connection of the VANET, therefore meeting the criteria for expanded services, which include commercial, informational, and safety applications.

3 The Architecture of Vehicle to Vehicle Communication:

Vehicle ad hoc networks (VANETs) within intelligent transportation networks (ITSs) are especially used with reference to the IEEE 802.11p Ethernet standard. Applications involving autos notably call for the wireless connectivity it offers. Designed for vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) uses, the standard operations belong to the 5.9 GHz radio frequency range [12]. Because it can provide low-latency, high-speed data networks—necessary for real-time applications like synchronized signals for traffic control and collision avoidance—the IEEE 802.11p normal is an important reference. In high-speed situations like cars [13], the ability of the protocol to quickly create a communication channel and replace the need for many handshakes might be rather important.

The QoS mechanisms of IEEE 802.11p enable the prioritization of safety messages over less essential traffic. IEEE 802.11p serves as the basis for Dedicated Short-Range Communications (DSRC) technologies and standards pertaining to vehicular communication [14]. DSRC enhances security, reliability, and interoperability via the use of 5.9 GHz. Information processing, electronic fee collecting, and traffic control are applications related to both safety and non-safety aspects. The regulation of message flow by DSRC systems aims to safeguard communications, vehicles, and equipment against vandalism and threats [15]. Moreover, DSRC channelization enhances frequency spectrum usage, facilitating continuous simultaneous communications. DSRC is regarded as a pivotal technology in modern Intelligent Transportation Systems (ITS) because to its remarkable design capabilities, minimal latency, and excellent communication reliability [14]. To improve productivity, traffic density, and road safety, the use of V2V and V2I in smart transportation is essential.

Figure 1 demonstrates the interaction involving On-Board Units (OBUs) along automobiles as well as Road Side Units (RSUs) along roads, which help infrastructure and communication. It manages labor, operations, and transportation from and to central control as well as administrative locations. The modified hyper structure below may demonstrate the V2V communication structure and how elements interact for secure and efficient transmission. The most relevant V2V design for real-world applications must be shown. We explain how various designs improved V2V communication. Architectures include decentralised mesh the network, V2V-based clouds integration hub, Edge computing-based V2, Blockchain-enabled V2, V2V over hybrids cellular including ad-hoc networks, AI-assisted network design for V2V communication, and V2V support for sustainable transport systems V2V architectures work differently to handle vehicle interaction and vehicle management challenges, yet they complement one other. Rigorous research and integrating these ideas will yield dependable and efficient V2V systems for security, effectiveness, and environmental gains.

4 Distributed Mesh Networks

Each automobile operates as a sentinel inside the expansive communication network of a Distributed Mesh Network (DMN) that proliferates among nodes with advanced vehicular capabilities. Wireless protocols, such as IEEE 802.11p, enable communication among cars within the framework of short-range interactions, which is crucial for safety. Intermediate vehicles augment the network's coverage, guaranteeing that no area remains disconnected [17]. The advantage of decentralised is that no one entity has complete authority over the network. Each vehicle within the network takes advantage of the system's comprehensive resilience, which is characterized by its ability to respond to failures and sustain continuous communication. End-to-end encryption safeguards essential data from prying eyes, notwithstanding the significant security risk. The establishment of trust mechanisms enhances the network's resilience against the schemes of malicious entities. It can now authenticate incoming

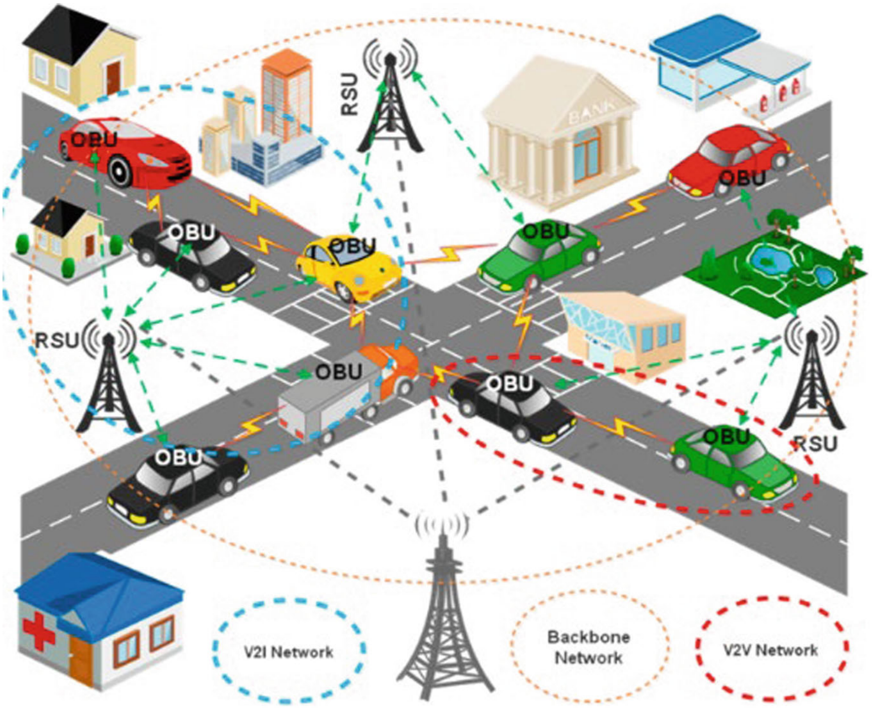

Fig. 1 Architecture structure of vehicle to vehicle communication [16]

messages and validate them using a recognition node. In a future when communication transcends boundaries, the richness and variety of the DMN will converge to provide security, dependability, and resilience [18]. The infrastructure can accommodate various vehicle volumes depending on the conditions due to its inherent scalability.

5 Vehicle to Vehicle (V2V) Communication Based on Cloud Computing

Modern cloud-integrated V2V hubs amalgamate cloud computing with vehicular communication. Vehicles send critical data in real time using communication modules. The hub utilizes cloud-based analytics to examine patterns, forecast traffic, and get insights for effective traffic management. This facilitates vehicular communication and global networking, irrespective of distance [19]. Decentralized communication enables low-latency interaction for safety–critical applications, whereas cars use peer-to-peer communication for immediate transfers. End-to-end encryption protects sensitive data from alteration. Only authorized individuals are allowed to view V2V communication information when cars log into the site. Edge computing facilitates the rapid processing of time-sensitive data by nodes, therefore decreasing the response time of safety–critical applications and enabling statistical analysis for traffic management [20]. A cloud-integrated V2V Hub, characterized by robustness and elegance, efficiently controls vehicle communications in a well-structured environment.

6 Vehicle to Vehicle (V2V) Communication Based on Edge Computing

Edge computing nodes situated at the network interface enable the processing of real-time V2V communication data. To alleviate latencies in applications that require safety, these periphery network nodes oversee time-sensitive data. Real-time examination of V2V communication data enhances decision-making. Edge computing decreases cloud server traffic and improves responsiveness by transferring processing tasks nearer to the data origin [21]. The system employs dynamic load-balancing to allocate processing workloads to external computer nodes. Short-range protocols provide communication between proximate vehicles without reliance on cloud resources. Dynamic automobile mesh networks may improve communication and dependability in low-line-of-sight conditions by using edge computing architecture. V2V data is secured and verified by computing nodes [22]. Intrusion detection systems identify security flaws. Real-time perimeter processing mitigates crashes and warnings by assessing the velocity and closeness of vehicles. Under intricate traffic circumstances, our system swiftly evaluates V2V data at intersections, therefore improving navigation and reducing the likelihood of collisions. Edge-based analytics use real-time vehicle tracking information to synchronize traffic lights, hence reducing congestion. The integration of online resources with peripheral computing facilitates real-time processing, enhanced analytics, and data archiving. This decentralized method enhances resources economy, real-time decision-making, as well as IoT-connected automobile performance [23].

7 Vehicle to Vehicle (V2V) Communication Based on Block Chain

A distributed blockchain relies on each linked automobile, which acts as a node. Decentralization diminishes central authority and promotes transparency. Employ smart contracts, that are contractual agreements that operate autonomously and are preordained. Automated and trustless vehicle-to-vehicle interactions are facilitated by smart contracts. Each V2V interaction signifies a transaction. Traffic data and safety alerts are among the activities confirmed by blockchain consensus mechanisms. Verified transactions are recorded on a public, immutable ledger. The blockchain's ledger protects vehicle data against alteration. Vehicles engage in real-time peer-to-peer data exchange, while the blockchain preserves transaction records. These actions are securely recorded via the blockchain [24]. Employ encryption to authenticate vehicle communications and transactions. Cryptographic hashes ensure data integrity, while the use of public keys authenticates vehicle identities and facilitates consensus mechanisms like Proof of Work (PoW) or Proof of Stake (PoS) for transaction validation. The integrity of the blockchain is maintained by the incorporation of just authentic transactions via consensus. It enables private transactions that utilize zero-knowledge proofs [25]. This facilitates the clandestine transfer of information between vehicles. V2V systems, enabled by blockchain technology, assign aliases to vehicles. Blockchain transactions are recorded while vehicle identifiers are concealed. Vehicle traffic alerts and safety notifications are authenticated by blockchain technology [26]. Besides improving road safety, verified warnings also function to prevent misinformation. Consequently, blockchain accident records are immutable. This information is essential for insurance claims, law enforcement, and post-accident investigations.

8 AI-Optimized VANETs

Integrated architectures, applications, routing, safety allocation of resources and access innovations, portability management, and management of mobility are the six topics that are examined in this part. These are all areas that may benefit from artificial intelligence technology.

VANET applications: One of the most often used uses of VANET facilitates the timely response to particular occurrences and assures safe travel via the transmission of early alerts. Applications of VANET may be categorized into three main categories.

- Protection applications: VANET applications broadcast danger and obstacle information to prevent automobile collisions. Random forest algorithms may forecast crashes. Drivers must weigh numerous criteria while choosing a route. Traffic lights, pedestrians, autos, and GPS guidance are examples. This makes it hard for drivers to multitask. In this setting, analyzing driver behavior is crucial. Because it provides reliable and timely information, a Support Vector Machine may assist detect road conditions. Convolutional Neural Networks forecast driving behavior to prevent risky maneuvers [27]. Safety apps are utilized for lane change management, navigation, and automated emergency brakes to avoid crashes. These applications may be enabled by using Principal Component Analysis to extract important input data from driver qualities, automobile properties, and environmental characteristics [28].
- Application in Traffic management: Traffic management include strategies to optimize traffic flow, reduce travel time by the elimination of bottlenecks, and inform drivers of current road conditions along the most efficient routes. Reinforcement

learning may be used to control e-sign panels and intricate traffic signals on highways. The reduced processing cost and simplified gating structure enable GRU, a kind of RNN, to predict local highway traffic flow. LSTM has superior predictive accuracy compared to conventional time series networks, making it potentially more effective for traffic forecasting. Larger datasets enhance LSTM performance compared to conventional time series models; they also expedite processing and improve handling capabilities. Comprehending traffic congestion would facilitate capacity enhancement and alleviation. ACO swarm intelligence potentially mitigates traffic congestion via traffic flow control [29]. Due to their closely connected processing components, CNN and ANN models provide exceptional predictive accuracy and contribute to congestion mitigation. KNN can forecast vehicular density and velocity at various periods of the day. In conditions of minimal error, KNN surpasses both the tree model and linear regression of the input data [30]. Machine learning may enhance traffic management initiatives by taking into account road factors such as weather.

Routing Application: Routing is essential in VANETs since all supported services need multi-hop connections. Gaming and file transfer need unicast connections. Multicasting occurs during collision alerts and platooning. The routing in VANET is hampered by the variability in vehicle velocity in urban as well as highway settings. Variations in speed may damage vehicle communication systems. Obstructions and modifications in the express lane are other issues. It is crucial for most routing systems, especially those with several hops, to choose quasi-optimal relays. The use of an SVM classifier for node classification based on message transmission, alongside Random Forest for analyzing the vehicle's vicinity, may enhance automobile routing protocols [31]. LSTM [32] ensures the dependability of vehicle routing by stochastically forecasting traffic flow and maintaining vehicle information. Research on behavior of drivers indicates that CNN can anticipate future driving paths to reduce the need for quick modifications in case of a route breakdown. ACO is an efficient technique for identifying the quasi-shortest path in data routing, but DT and NB may also be utilized [33]. The bioinspired ACO has the capability to self-organize, recuperate from failures, and discern the nearly optimal solution. Particle Swarm Optimization (PSO) may be used by geocast methods to detect neighboring cars within a designated area. No particles in the PSO algorithm operates autonomously of its neighbors as it moves toward the most prominent places in the search space, which evolve as other particles identify more favorable spots. This should aid the swarm in recognizing semi-optimal options.

Safety allocation of resources: Security in VANETs has been extensively researched during the last decade. Vehicles and roadside structures are interconnected via VANETs. The safety of these essential contacts is crucial. Consider the integrity, trustworthiness, and relevance of additional automobile communications including real-time safety application needs. As previously mentioned, cars convey safety information via VANETs and make essential choices based on the data in their surroundings. Passengers in the vehicle may be jeopardized if this information is erroneous. VANET users may misread vehicle, the environment, and road circumstances.

Sybil attacks are a method of traffic manipulation when car nodes replicate bottlenecks. Vehicle security concerns include malicious nodes, DDoS attacks, authentication and confidence management, SQL injections, malware prevention and identification, and hardware attacks across physical, network, the application, and cloud layers. K-means is a suitable method for initial node clustering to detect malicious nodes, since it adjusts to the changing topology of VANET. Exercise vigilance on CAN bus attacks and other vehicular infractions. Deep learning is essential for detecting intrusions using GRU, a network of recurrent neural networks. Utilizing GRU's distributed cooperative architecture, vehicle nodes may assess network circumstances and decide in real time whether to counteract jamming attacks, thereby averting communication interruptions [34]. Artificial Neural Networks detect wrongdoing by categorizing nodes according to their previous behavior. CNNs with back-propagation can extract spatio-temporal vehicle characteristics using a two-dimensional dataset. LSTM [32] identifies OBU malware by the analysis of temporal network traffic data. This study proposes several trust management solutions to assure the trustworthiness of VANET data and nodes. In an automotive network, an automobile may assess the dependability of a communication by evaluating the reliability of the transmitting vehicle, the perspectives of those around it, and its prior encounters with the communication vehicle. Automobile mobility interrupts and truncates conversations. The swift validation of emergency alerts is a formidable challenge. Vehicular nodes in VANET and third-party trust may be generated by SVM and RL. Support Vector Machine (SVM) is a dependable technique for non-linear classification. The vehicle's inputs as well as attributes make it an outstanding tool for trust modeling. The effectiveness is shown in many vehicles. Reinforcement Learning [35] may evaluate trust by analyzing comprehensive vehicle data and historical acts. Identify and alleviate established DoS assaults. By understanding the operation of vehicle clusters, PSO can alleviate DoS attacks. The PSO particle search space is used in VANET vehicles. Subsequently, modify the search parameters for particle historical behavior.

The continual deployment of decision-making skills using artificial intelligence (AI) techniques—which include deep learning (DL) as well as machine learning (ML)—helps VANET operate as it should. Artificial intelligence's capacity to assess vast volumes of real-time information and adapt to changing conditions places it particularly in a position to address the fundamental problems with VANETs.

- AI for Route Optimization

  By avoiding crowded network paths and identifying possible congestion locations, AI-driven VANETs help to effectively transmit data. Using reinforcement learning methods, routing systems dynamically change real-time traffic patterns [36].
- AI in Traffic Prediction

  To make wise judgments, autonomous cars depend on knowledge about traffic density and travel patterns. By means of analysis of both historical and present data, artificial intelligence models using LSTM (Long Short-Term Memory) systems are able to forecast traffic patterns [37].
- Security and Privacy Considerations in AI

Given the possibility for breaches, security causes a major worry inside VANETs. By identifying and halting malicious activity in real time, blockchain technology and AI-powered intrusion detection systems (IDS) can make VANETs safer [38].By identifying and halting malicious activity in real time, blockchain technology and AI-powered intrusion detection systems (IDS) can make VANETs safer.

- AI in Adaptive Communication

  Artificial intelligence shapes defined priorities and thereby influences the allocation of network resources by means of current network circumstances. For example, non-essential information is subordinated to crucial notifications like collision warnings.

9 Conclusion

The researcher conducted an investigation of artificial intelligence algorithms for pedestrian safety applicable to VANETs in this work. This section has examined several artificial intelligence methodologies. The efficacy of automotive programs may be enhanced by the use of AI-driven algorithms rather than conventional methods. The performance optimization challenge in many areas sometimes presents several difficulties due to opposing considerations. Thus, the fields of artificial intelligence, deep learning, as well as machine learning may synergize to provide optimal solutions that conform to the constraints of these technologies. Typically, artificial intelligence algorithms entail more computing expenses and need more resources than other algorithms. These gadgets may not be integrated into vehicles or the units located next to the roadway. Delegating certain calculations to exterior processing and storage servers located in the fog, cloud, or edge reduces the computational strain on artificial intelligence systems. The recent emergence of novel integrated architectures and accessibility methods, such fog and edge computing, may mitigate this strain. Consequently, researchers have demonstrated how certain AI methodologies may use the advantages of the VANET the surroundings, despite the constraints associated in some AI processes.

References

1. Alen Joseph Samuel, S.S.: An algorithm for IoT based vehicle verification system using RFID. Int. J. Electr. Comput. Eng. **9**, 3751–3758 (2019)
2. Zhenyu, L., Lin, P., Konglin, Z., Lin, Z.: Design and evaluation of V2X communication system for vehicle and pedestrian safety. J. China Univ. Posts Telecommun. **22**(6), 18–26 (2015)
3. Dzulkurnain, Z., Saon, A.K.M.S., Ahmadon, M.A., Yamaguchi, S.: Internet of things (IoT) based traffic management & routing solution for parking space. Indonesian J. Electr. Eng. Comput. Sci. (2019)

4. Xia, S., de Godoy Peixoto, D., Islam, B., Islam, M.T., Nirjon, S., Kinget, P.R., Jiang, X.: Improving pedestrian safety in cities using intelligent wearable systems. IEEE Internet Things J. **6**, 7497–7514 (2019)
5. Gandhi, T., Trivedi, M.: Pedestrian protection systems: issues, survey, and challenges. IEEE Trans. Intell. Transp. Syst. **8**(3), 413–430 (2007)
6. Silva, C., Silva, L., Santos, L., Sarubbi, J., Pitsillides, A.: Broadening understanding on managing the communication infrastructure in vehicular networks: customizing the coverage using the Delta Network. Future Internet **11** (2018)
7. Arena, F., Pau, G.: An overview of vehicular communications. Future Internet (2019)
8. Song, F., Zhou, Y., Wang, Y., Zhao, T., You, I., Zhang, H.: Smart collaborative distribution for privacy enhancement in moving target defense. Inform. Sci. **479**, 593–606 (2019)
9. Self-Driving Car (2022). Available online: https://en.wikipedia.org/w/index.php?title=Self-driving_car&oldid=1117961929
10. Arif, M., Wang, G., Bhuiyan, M.Z.A., Wang, T., Chen, J.: A survey on security at-tacks in VANETs: communication, applications and challenges. Veh. Commun. **19**, 100179 (2019)
11. Harounabadi, M., Soleymani, M.D., Bhadauria, S., Leyh, M., Roth-Mandut, V2X in 3GPP standardization: NR sidelink in rel-16 and beyond. IEEE Commun. Stand. Mag. (2021)
12. Ansari, K.: Joint use of DSRC and C-V2X for V2X communications in the 5.9 GHz ITS band. IET Intell. Transp. Syst. **15**, 213–224 (2021)
13. Masini, B.M., Bazzi, A., Zanella, A.: A survey on the roadmap to mandate on board connectivity and enable V2V-based vehicular sensor networks. Sensors **18**, 2207 (2018)
14. Al-Absi, M.A., Al-Absi, A.A., Lee, H.J.: Comparison between DSRC and other short range wireless communication technologies. In Proceedings of the 2020 22nd International Conference on Advanced Communication Technology (ICACT), pp. 1–5. Phoenix Park, Republic of Korea (2020)
15. Azzaoui, N., Korichi, A., Brik, B., Fekair, M.E.A., Kerrache, C.A.: Wireless communication in internet of vehicles networks: DSRC-based Vs cellular-based. In: Proceedings of the 4th International Conference on Smart City Applications, Casablanca, Morocco, pp. 1–6 (2019)
16. Muslam, M.M.A.: Enhancing security in vehicle-to-vehicle communication: a comprehensive review of protocols and techniques. Vehicles **6**(1), 450–467 (2024)
17. Ernst, J., Wang, Z.D., Abraham, S., Lyotier, J., Jensen, C., Quinn, M., Harvey, D.A.: Decentralized Mobile Mesh Networking Platform Powered by Blockchain Technology and Tokenization. RightMesh AG, White Paper (2019)
18. Salama, A., Stergioulis, A., Hayajneh, A.M., Zaidi, S.A.R., McLernon, D., Robertson, I.: Decentralized federated learning over slotted aloha wireless mesh networking. IEEE Access **11**, 18326–18342 (2023)
19. Fong, B., Fong, A.C., Hong, G.Y.: Sustainable micromobility management in smart cities. IEEE Trans. Intell. Transp. Syst. **24**, 15890–15896 (2023)
20. Wan, J., Chen, B., Wang, S.: Smart Manufacturing Factory: Artificial-Intelligence-Driven Customized Manufacturing. CRC Press, Boca Raton (2023)
21. Naeem, M.A., Zikria, Y.B., Ali, R., Tariq, U., Meng, Y., Bashir, A.K.: Cache in fog computing design, concepts, contributions, and security issues in machine learning prospective. Digit. Commun. Netw. **9**, 1033–1052 (2023)
22. Meng, Y., Naeem, M.A., Almagrabi, A.O., Ali, R., Kim, H.S.: Advancing the state of the fog computing to enable 5G network technologies. Sensors **20**, 1754 (2020)
23. Wang, H., Liu, T., Kim, B., Lin, C.-W., Shiraishi, S., Xie, J., Han, Z.: Architectural design alternatives based on cloud/edge/fog computing for connected vehicles. IEEE Commun. Surv. Tutor. **22**, 2349–2377 (2020)
24. Khan, A.S., Balan, K., Javed, Y., Tarmizi, S., Abdullah, J.: Secure trust-based blockchain architecture to prevent attacks in VANET. Sensors **19**, 4954 (2019)
25. Mollah, M.B., Zhao, J., Niyato, D., Guan, Y.L., Yuen, C., Sun, S., Lam, K.-Y., Koh, L.H.: Blockchain for the internet of vehicles towards intelligent transportation systems: a survey. IEEE Internet Things J. **8**, 4157–4185 (2020)

26. Oham, C., Michelin, R.A., Jurdak, R., Kanhere, S.S., Jha, S.: B-FERL: blockchain based framework for securing smart vehicles. Inf. Process. Manag. **58**, 102426 (2021)
27. Zhao, H., Cheng, H., Mao, T., He, C.: Research on traffic accident prediction model based on convolutional neural networks in VANET. In: 2019 2nd International Conference on Artificial Intelligence and Big Data (ICAIBD), pp. 79–84. IEEE (2019)
28. Soon, F.C., Khaw, H.Y., Chuah, J.H., Kanesan, J.: Semisupervised PCA convolutional network for vehicle type classification. IEEE Trans. Veh. Technol. **69**(8), 8267–8277 (2020)
29. Khoza, E., Tu, C., Owolawi, P.A.: Decreasing traffic congestion in VANETs using an improved hybrid ant colony optimization algorithm. J. Commun. **15**(9) (2020)
30. Rasyidi, M.A., Kim, J., Ryu, K.R.: Short-term prediction of vehicle speed on main city roads using the k-nearest neighbor algorithm. J. Intell. Inf. Syst. **20**(1), 121–131 (2014)
31. Srinidhi, N.N., Sagar, C.S., Shreyas, J., Dilip Kumar, S.M.: An improved PRoPHET-random forest based optimized multi-copy routing for opportunistic IoT networks. In-ternet Things **11**, 100203 (2020)
32. Singh, U., Gupta, P., Shukla, M.: Activity detection and counting people using mask-RCNN with bidirectional ConvLSTM. J. Intell. Fuzzy Syst. **43**(5), 6505–6520 (2022)
33. Nadarajan, J., Kaliyaperumal, J.: QOS aware and secured routing algorithm using machine intelligence in next generation VANET. Int. J. Syst. Assur. Eng. Manag. (2021)
34. Otoum, S., Kantarci, B., Mouftah, H.: Empowering reinforcement learning on big sensed data for intrusion detection. In: ICC2019–2019 IEEE International Conference on Communications (ICC), pp. 1–7. IEEE (2019)
35. Zhang, D., Yu, F.R., Yang, R., Zhu, L.: Software-defined vehicular networks with trust management: a deep reinforcement learning approach. IEEE Trans. Intell. Transp. Syst. (2020)
36. Kumar, D., Kumar, A.: A reliable hybrid autoregressive integrated moving average and deep reinforcement machine learning strategy for resiliency enhancement in microgrid. Sustain. Energy Grids Networks **39**, 101424 (2024)
37. Le, T.D., Kaddoum, G.: LSTM-based channel access scheme for vehicles in cognitive vehicular networks with multi-agent settings. IEEE Trans. Veh. Technol. **70**(9), 9132–9143 (2021)
38. Kumar, G., Altalbe, A.: Artificial intelligence (AI) advancements for transportation security: in-depth insights into electric and aerial vehicle systems. Environ. Dev. Sustain. 1–51 (2024)

Real-Time Surveillance System to Monitor Vehicles and Pedestrians for Road Traffic Management

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Abstract Accurately monitoring pedestrian and vehicular flow is crucial for traffic management, urban planning, and public safety. Conventional approaches fail to provide greater performance in both accuracy and efficiency. This study used a deep learning object identification model like YOLOv9 to recognize and track pedestrians and cars in real-time video streams. Furthermore, this methodology goes beyond simple detection by integrating speed estimation capabilities. Examining consecutive frames and applying motion estimation techniques helps to estimate the speed of found vehicles precisely, so augmenting our knowledge of urban dynamics. Apart from counting the cars and pedestrians crossing the camera, it can recognize vehicles and objects. Results of tests on benchmark datasets show the value of the suggested method, which surpasses present methods in terms of accuracy, precision, recall, and mean average precision.

Keywords Computer vision · Pedestrian detection · Object detection · Road traffic management · Speed estimate · Surveillance · Vehicle detection

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1 Introduction

Modern urban environments depend critically on efficient traffic control both for pedestrians and vehicles. This is so because it is required for the seamless running of transport systems, so enhancing public safety, and so supporting urban planning projects. Meeting these targets depends critically on accurate counting of people and vehicles as well as exact estimate of their speeds [1]. Conventional methods for these kinds of projects usually lack scalability, accuracy, and relevance to metropolitan environments. Current approaches for automated vehicle and pedestrian counts combine several technologies. These technologies have shortcomings including undercounting due to occlusion and the difficulty to distinguish between various types of pedestrians even if they are more accurate and offer continuous data collecting than hand counting. Successful pedestrian counting programs are further challenged by factors including as occlusion-related errors, the difficulty of finding suitable sites and technologies, and ignorance of pedestrian traffic patterns.

This work presents a unique approach using deep learning techniques with traditional image processing methods to solve these problems and forward the field of traffic management by transforming vehicle and pedestrian counting as well as speed estimate in urban environments. Although our approach mostly depends on the use of You Only Look Once version 9 (YOLOv9) [2], our main aim is to build a complete system for YOLOv9 model-based road transport analysis. The main objectives of this work are to show how effective an integrated approach is at identifying and counting both pedestrians and vehicles, to develop a system for estimating vehicle speeds [3] using distance calculations, and investigate the several uses of both speed estimation and vehicle and person counting in a variety of fields, including traffic management, Intelligent Transportation Systems (ITS), public safety, surveillance systems, and retail. The proposed method guarantees the supply of accurate and reliable data for traffic research by functioning well even under demanding conditions, such variations in lighting, temperature, and obstacles [4].

Including speed estimating features into this system aims to provide valuable data for urban planning, traffic management, and safety enforcement projects. Perfect vehicle and human counting has a great variety of possible applications when combined with speed estimate. On lane allocation, signal timing, and traffic flow optimisation, these characteristics can support traffic management decisions. For public safety, they enhance traffic enforcement and emergency reaction strategies [5]. This work will review the methodology and implementation of our project, present the results, and discuss the several applications and consequences of the built system. The work presented in this chapter advances computer vision (CV), machine learning (ML), deep learning (DL), and transportation systems so increasing the efficacy and security of urban transportation networks.

1.1 Research Gaps

- Modern algorithms like YOLOv9 excel in real-time identification but struggle with variations in lighting, different weather conditions, and occlusions.
- Current speed estimation algorithms face challenges due to occlusions, non-standard vehicles, and fluctuating vehicle speeds.
- The current systems rely on predefined speed thresholds which may be oversimplified.

1.2 Key Contributions

The main contributions of this work are on creating a thorough system for exact vehicle and pedestrian counts, over-speed detection in metropolitan environments, and consistent speed estimations. Not to show the YOLOv9 model; rather, the main objective is to address the critical traffic management issues using advanced CV and DL techniques.

- Combining a specifically trained YOLOv9 model with traditional image processing methods, the proposed system detects and counts cars and people in a range of urban environments with a mean Average Precision (mAP) of 85%.
- The system detects cars exceeding the speed limit in addition to estimating speed using centroid tracking and bounding box centers as its basis.
- The system uses perspective transformation techniques to get over the viewpoint distortion in surveillance video.
- By means of pedestrian and vehicle counts, speed computation, and over-speed detection into a single system, one offers a whole traffic management and urban planning solution.

1.3 Challenges

Developing advanced surveillance systems calls for overcoming several challenges to ensure dependability and accuracy of operation. The intricate and dynamic backgrounds seen in many surveillance situations can significantly influence the efficiency of object detection and tracking systems. Occlusion that is, when objects are somewhat hidden makes tracking constantly and precisely rather difficult. In metropolitan settings especially, this is especially evident when there are many cars or people. Good surveillance systems have to operate under a range of lighting and weather conditions, including strong rain, fog, and brilliant sunlight. These variations could influence the visibility and appearance of an object, so challenging detection systems to remain accurate.

Timely action and decision-making depend on real-time processing of surveillance data. But in high-resolution video streams especially, real-time performance calls for a lot of processing capability and well-tuned algorithms. Scalability becomes further difficult as surveillance systems expand to cover more sites or areas. To overcome these obstacles, constant research and development is needed to raise the ethical criteria, accuracy, and robustness of surveillance systems. Through addressing critical problems in vehicle and pedestrian counts, speed estimate, and over speed detection, this work advances traffic management, public safety, and urban planning initiatives. More intelligent and sustainable urban environments open the possibility of significant impact on CV, machine learning, and transport systems depending on the outcomes of this study.

2 Literature Survey

Dai et al. [6] present a framework for YOLOv3-based vehicle object identification. It tracks objects by means of the KCF algorithm, deriving trajectories and matching templates. This framework is developed and evaluated on a particular Vehicle Object Detection (VDD) dataset. The obtained trajectories offer spatiotemporal data on vehicle movement. Operating on the VDD at a speed of 20.7 fps, the model had an overall accuracy of more than 90%.

Shami et al. [7] proposed convolutional neural networks (CNNs) as a means of spotting sparse heads in images of packed crowds. After splitting images into patches, they classify crowd patches using a binary classifier based on speeded-up robust features (SURF). The average head size in every patch is then estimated using regression; the number of people is computed by dividing the patch area by the projected head size. Should no heads be found in the patch, they employ weighted averages derived from surrounding patches depending on distance. Especially images of highly dense crowds, their approach produces result on publicly available datasets for highly dense crowds that are equivalent to state-of- the-art methods without the need of labelled training data. Yang et al. [8] presented a technique for quick and accurate traffic volume estimate and vehicle counting in traffic videos. They employ an attention-based TSI density map estimation network to count the vehicles after converting videos into time-spatial images (TSIs) and manually marking the vehicle placements. The UA-DETRAC dataset findings show how effective the method is at balancing speed and accuracy, even with small amounts of video data.

A pipeline based on vision was proposed by Liu et al. [9] to derive traffic statistics from camera footage that has been preserved. Their technique uses object detectors with transfer learning to recognize vehicles, bicycles, and pedestrians in monocular video streams. Using image-to-world homography and weak camera calibration, the system calculates the length and speed of vehicles, counts the number of cars in each lane, and uses projective geometry in conjunction with a CNN to classify vehicles. The pipeline effectively processes 60 frames per second, producing high-quality data for traffic analysis, and has been tested on recordings from various locations. In order to improve traffic monitoring, Xiang et al. [10] used aerial footage taken by unmanned aerial vehicles (UAVs) to create a model for vehicle counting. Their technology uses a moving-object detector to handle both static and dynamic background circumstances. To detect automobiles on static backgrounds, a pixel-level foreground detector is used to continuously update the background model. Image registration detects cars inside a reference coordinate system by estimating camera motion in situations with moving backgrounds. Vehicle counting tests using actual highway sceneries demonstrated an accuracy of over 90% for static backgrounds and 85% for dynamic settings.

In order to improve vehicle counting and categorization, Lin et al. [11] suggested a real-time traffic monitoring system that integrates a virtual detection zone, GMM, and YOLO. Datasets such as MAVD and GRAM-RTM are used to validate the model. The suggested approach performs well under a variety of circumstances and attains a high classification accuracy. Having an average absolute percentage error of about 7.6%, it also achieves precise vehicle speed prediction. Lin and Jhang [12] put out a vehicle counting method using a modified YOLOv4-tiny for detection and a multi-object counting technique. The upgraded YOLOv4-tiny architecture added three outputs to increase detection accuracy while the multi-object counting method, which used Kalman filters and the Hungarian algorithm, linked and matched cars across frames to avoid double counting. Our approach addressed the challenge of precisely counting vehicles in continuous image frames so guaranteeing a reliable collection of vehicle information for later analysis in traffic applications.

Sambolek et al. [13] evaluated the dependability of many state-of- the-art detectors including YOLOv4, Faster R-CNN, RetinaNet, and Cascade R-CNN in search and rescue efforts. The performance of these detectors was assessed using the VisDrone benchmark and a specifically created dataset called SARD, meant to replicate rescue scenarios. Examining elements like network resolutions, detection accuracy, and transfer learning parameters helped them to improve these detectors for person detection under SAR conditions. They also looked at how robust the YOLOv4 model was to bad weather and motion blur in order to offer a better model for SAR operations. Pang et al. [14] presented a novel technique for precisely counting vehicles in several-vehicle occlusions within monocular traffic image sequences. The method produces individual contour descriptions, counts the vertices per car, and assigns a resolvability index to every occluded vehicle using a deformable and contour description model. The method revealed 100% vehicle counting accuracy and lowered root-mean-square errors in vehicle size estimate when tested using real-world traffic images.

Tayara et al. [15] proposed manually created feature extracting and classification methods for aerial vehicle detection. They selected areas using supervised classification then obtained SIFT features and applied SVMs for classification. A further approach involved region selection, Histogram of Gradient (HOG) feature extraction, and discrimination using a variety of methods, including SVM and mutual information measure. For quick vehicle orientation and type identification, a two-stage approach—binary sliding window detection and multi-class classification—was used. They combined nonlinear filtering, feature reduction, and Gaussian process regression for detection. Other methods included combining local and global vehicle data, road and vehicle alignment using HOG and SVM/Viola-Jones integration, and super pixel segmentation. Additionally, increased entropy rate clustering (IERC) and correlation-based sequential dictionary learning (CSDL) were used for dictionary updating.

A method for identifying and counting automobiles in high-resolution UAV images was proposed by Moranduzzo and Melgani [16]. Before employing the scalar invariant feature transform to extract features, they first screen asphalted zones to remove false alarms. In order to create a “one key point-one car” relationship, an SVM classifier first isolates automotive key points from other types of points. A promising car counting accuracy of 76.61% is shown by the experimental findings on real UAV scenes with a spatial resolution of 2 cm. By using cutting-edge CV approaches to extract traffic data from recorded movies, Unzueta et al. [17] offered a creative way to use outdated camera systems in traffic management. To identify things, its vision-based pipeline transfers learning and integrates state-of-the-art object identification models. They accomplish vehicle counts by lane and accurate vehicle speed estimations in real-world units by using a new combination of image-to-world homography and weak camera calibration. Vehicle identification is further improved using a classification module that combines projective geometry and a CNN. The technology, which has been tested in a variety of traffic scenarios, can process videos at 60 frames per second and produces high-quality metadata that is on par with piezoelectric sensors, improving traffic analytic capabilities.

A Hybrid YOLOv4 model for crowd surveillance was trained by Khel et al. [18] using the JHU dataset, with an emphasis on predicting individual count, movement direction, and speed. They increased model efficiency by optimizing convolutional layer filters during training using L1 normalization-based pruning. Convolutional Block Attention Modules (CBAM) were part of this method to raise target detection accuracy. After analyzing the found data, the DeepSort tracker assigned unique IDs for simple tracking using bounding boxes. Zarei et al. [19] presented the FastYolo-Rec method to handle vehicle detection in the balance between speed and accuracy. Their method integrates a new Yolo with Long Short-Time Memory (LSTM) to increase detection efficiency and accuracy through SSAM by alternating prediction and detection frames, the technique preserves a reasonable degree of accuracy while accelerating real-time vehicle tracking. Testing on a road dataset shows how better their approach is than standard practices. Li et al. [20] proposed a time-span-based method for traffic volume estimate and vehicle counting bypassing conventional detection and tracking. Their solution beats current approaches when evaluated on the UA-DETRAC dataset. To improve road safety and reduce traffic, Tsai et al. [21] created a real-time system that uses DL approaches to recognize and count automobiles. Their technique combines lane-based counting and YOLO vehicle recognition, and out of multiple YOLO versions, YOLOv3-spp has the best precision, recall, and F1 ratings. The potential of deep learning for real-time traffic management was further supported by counting trials, where YOLOv3-608 outperformed YOLOv2, SSD, and other techniques to record the highest accuracy, precision, and F1 scores.

An extremely accurate vehicle counting method utilizing Mask R-CNN in conjunction with a KLT tracker was proposed by Ariny et al. [22]. The KLT tracker assigns trajectories to guarantee precise counting, while Mask R-CNN’s instance segmentation effectively recognizes cars, even in obscured circumstances. Their approach counts 76 out of 77 vehicles in a sample video and achieves 98.7% precision in differentiating between counted and new vehicles. The benefits of combining trajectory tracking and instance segmentation for complicated video situations are demonstrated in this study. A method for calculating speed and estimating distance in vehicle detection systems was presented by Vijayalakshmi et al. [23]. Their approach tracks with the Dlib package using a DeepSORT tracker, an SSD model for detection, and the Euclidean metric to compute speed depending on relative motion. Experimental data show that it has great tracking ability and outstanding detection accuracy, which qualifies it for real-time driving uses. With accuracy, F1 score, precision, and recall scores of 0.82, 0.85, and 0.80 respectively, the SSD model had a mean average precision (mAP) of 0.78.

Ahmad et al. [24] propose an understudied perspective in video surveillance: person detection from overhead views. They first trained the YOLO (You Look Only Once) deep learning model on frontal view datasets. They count people from overhead views using classified bounding box information as well. The YOLO model performed exceptionally well, with a 95% TPR with a negligible FPR of 0.2%. This study demonstrates how well YOLO works to overcome the difficulties caused by above views, providing viable answers for reliable person recognition in security cameras. Saxena et al. [25] used SSD and MobileNetV2 models to present a DL-based Vehicle Counting and Speed Estimation (VCSE) system for surveillance footage. While object tracking and speed estimation methods made use of detection output, object detection was enhanced through fine-tuning on a surveillance dataset. Speed estimation mistakes were decreased by over 2% through calibration using specialized videos. By monitoring speed restrictions, improving road safety, and fortifying security measures, the system demonstrated important applications in law enforcement, safety, and security. It earned a high mAP score of 0.88 for object detection and 98% accuracy for speed estimation.

Fang et al. [26] suggested Tinier-YOLO, an enhanced version of Tiny-YOLO-V3, to reduce model size without compromising detection accuracy or real-time performance. Tinier-YOLO enhances feature propagation while attaining a significant parameter reduction by integrating the SqueezeNet fire module and adding dense connections between fire modules. A passthrough layer mitigates the impact of model size decrease on detection accuracy. On Jetson TX1, Tinier-YOLO achieves a small model size of 8.9 MB while maintaining real-time performance of 25 frames per second, making it comparatively four times smaller than Tiny-YOLO-V3. Evaluation on the COCO and PASCAL VOC datasets demonstrates mAPs of 34.0% and 65.7%, respectively, with comparable performance to other lightweight components, suggesting promise for embedded device deployment.

In order to get over the difficulties in identifying small-scale pedestrians in photos, Wanye and Jinping [27] presented a sophisticated pedestrian recognition method based on Faster R-CNN. Their method clusters, finds pedestrian areas using a Regional Proposal Network (RPN), and employs a deep CNN for consistent feature extraction. They presented a unique multi-layer feature fusion method that cascades high- and low-level characteristics, improving the semantic information and hence refining detection. They also addressed sample imbalance using OHEM, so greatly increasing the detection accuracy. Experimental analyses on the PASCAL and INRIA pedestrian datasets revealed clear increases in average accuracy of 6.3% and 13.93%, respectively, so demonstrating the efficiency of their approach for spotting small-scale pedestrian targets. Using a cascade classifier and CNN, Satti et al. [28] proposed a system to identify the traffic signs in an Indian road and achieved outstanding performance in real time. Satti et al. [29] proposed a system to generate the real-time caption to an image using Resnet and LSTM (Table 1).

3 Proposed Methodology

3.1 Overview

Figures 1 and 2 present a sophisticated method for looking through video footage to locate and follow particular objects including people and vehicles. This operation consists of several crucial components that each are necessary for precise object tracking and detection. The arrival of video footage marks the first phase and shapes all further inquiry. Frame extraction comes next in breaking out the video into individual frames. This stage is essential because it allows for a thorough, frame-by-frame analysis of the video.

The technology can more accurately detect and track objects by analyzing each frame separately. After that, a pre-trained model is loaded, trained on enormous collections of tagged photos, and is capable of identifying a variety of items in the frames, including people and cars. This model receives every extracted frame for examination. The system detects and classifies objects in every frame it receives using the object recognition abilities of the model. Before the model handles the frame, a viewpoint change is used. This phase changes the perspective of the frame to suitably show objects in line with the training data of the model. Perspective transformation provides exact object detection when camera angles distort object dimensions.

The model detects objects in the frame from the point of view change. Should no objects be detected, the system immediately shifts to the next frame and repeats the process. If an object is discovered, though, the flowchart divides into two sections based on the type of object found either a car or a human. Should the object under identification be human, a tracker class is called. Monitoring the person's movements throughout consecutive frames falls under this class's purview. The system records the people it has found as well.

When managing access control in limited areas or crowd monitoring, where knowledge of the current number of people is essential, this counting system is useful. Should the identified object be a vehicle, a corresponding tracker class tracks the vehicle. Apart from monitoring and control of traffic, the system counts the found vehicles in addition to tracking. Moreover, the system determines the detected vehicle's speed. It generates useful information for traffic enforcement and safety

Table 1 Summary of recent works

Model	Dataset	Methodologies	Limitations
[1]	Vehicle object detection (VDD) dataset	Identify vehicle objects using YOLOv3, track objects with KCF algorithm	Requires dedicated VDD dataset, limited to vehicle counting and speed estimation
[2]	UCF_CC_50, ShanghaiTech, and AHU-crowd	Detect heads in dense crowd images, employ SVM-based classifier to label crowd patches, and estimate head count	Lack of labeled training data for dense crowd images
[3]	UA-DETRAC dataset	Utilize TSI density map estimation network with attention mechanisms for counting, validate on UA-DETRAC dataset	Limited video data
[5]	Custom dataset	Extract traffic data from legacy camera videos using object detectors and transfer learning techniques	Requires weak camera calibration, may not generalize well to all scenarios
[6]	Custom dataset	Count vehicles in UAV aerial videos, address static and moving background scenarios, validate on real highway scenes	Limited to aerial views, may not perform well in densely populated urban areas
[7]	MAVD and GRAM-RTM datasets	Integrate virtual detection zones, GMM, and YOLO for vehicle counting and classification, then evaluate on MAVD and GRAM-RTM datasets	May not generalize well to all traffic scenarios, and requires calibration for accurate speed estimation
[8]	GRAM-RTM data set	Utilize modified YOLOv4-tiny for detection and multi-object counting method for tracking, address the challenge of accurately counting vehicles	Limited to vehicle counting, may not perform well in crowded traffic scenarios
[9]	VisDrone benchmark and SARD dataset	Evaluate Faster R-CNN and YOLOv4 in SAR scenarios and analyze transfer learning	Limited to SAR scenarios, may not generalize well to other applications
[10]	Custom dataset	Develop a method for counting vehicles in occlusions, utilize deformable and contour description model	Limited to counting vehicles in occlusions, may not generalize well to all traffic scenarios
[11]	Munich and overhead imagery research data set	Propose handcrafted feature extraction and classification strategies for aerial vehicle detection, validate various techniques	Limited to aerial views, may not generalize well to all traffic scenarios

(continued)

Table 1 (continued)

Model	Dataset	Methodologies	Limitations
[12]	Custom dataset	Detect and count vehicles in HD UAV images using feature extraction and an SVM classifier	Limited to high-resolution UAV photos, may not generalize well to lower resolution or different scenarios
[13]	Custom dataset	Extract traffic data from captured videos using computer vision techniques, validate on various sites, and compare with piezoelectric sensors	Requires weak camera calibration, may not generalize well to all scenarios
[14]	JHU dataset	Train hybrid YOLOv4 model for crowd surveillance, integrate L1 normalization-based pruning and DeepSort tracker	Limited to crowd surveillance, may not generalize well to other surveillance scenarios
[15]	CDNet2014 datase	Propose FastYolo-Rec algorithm for balancing accuracy and speed in vehicle detection, validate on highway dataset	Limited to vehicle detection, may not generalize well to other traffic scenarios
[16]	UA-DETRAC dataset	Develop a vehicle counting and traffic volume estimation method using a time-spatial structure, and validate it on the UA-DETRAC dataset	Focused on vehicle counting and traffic volume estimation, may not generalize to other traffic scenarios
[17]	Custom dataset	Propose real-time vehicle detection and counting system using YOLO, validate on various YOLO versions and SSD methods	Limited to vehicle detection and counting, may not generalize well to other traffic scenarios
[18]	e GRAM-RTM dataset	Introduce accurate vehicle counting approach using Mask R-CNN and KLT tracker, validate on various datasets	Limited to vehicle counting, may not generalize well to other tracking or detection scenarios
[19]	Custom dataset	Propose a method for speed calculation and distance estimation using SSD and DeepSORT models, validate on dedicated datasets	Limited to speed calculation and distance estimation, may not generalize well to other traffic scenarios
[20]	SOTON and IMS datasets	Introduce method for person detection from overhead views using YOLO, validate on various datasets	Limited to person detection from overhead views, may not generalize well to other surveillance scenarios

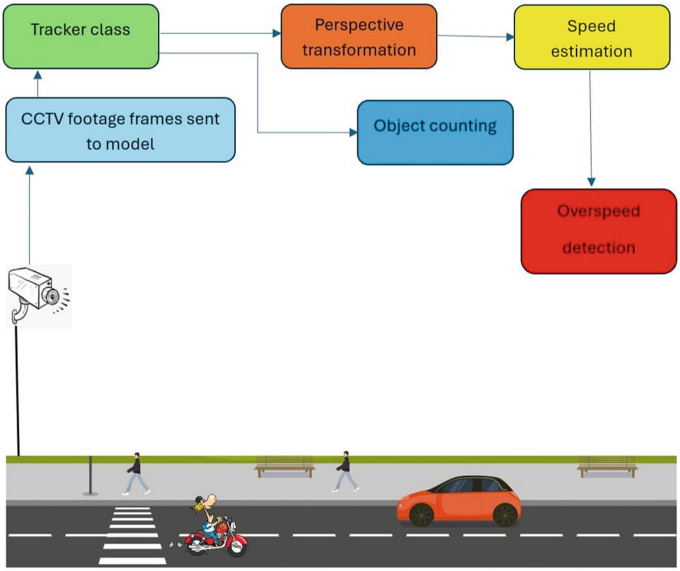

Tracker class
Perspective transformation
Speed estimation
CCTV footage frames sent to model
Object counting
Overspeed detection

Fig. 1 System architecture

analysis by tracking the vehicle's position over several frames and computing its velocity depending on the distance covered over time. Following current frame processing, the system looks for more frames to examine. Should extra frames exist, the process loops back to forward the next frame for analysis to the model. The process ends should no more frames be accessible.

3.2 Model Selection

Given the real-time demands of our application, we selected the YOLOv9. It fits our application well since it has shown remarkable speed and accuracy in many object identification challenges. We extensively preprocessed the video frames before to using the model in order to ensure YOLOv9's best possible input quality. This preprocessing stage consisted in several techniques including resizing, normalising, and noise reduction. We sought to standardise the resolution and enhance visibility in the video frames so raising the detection accuracy and robustness of the model.

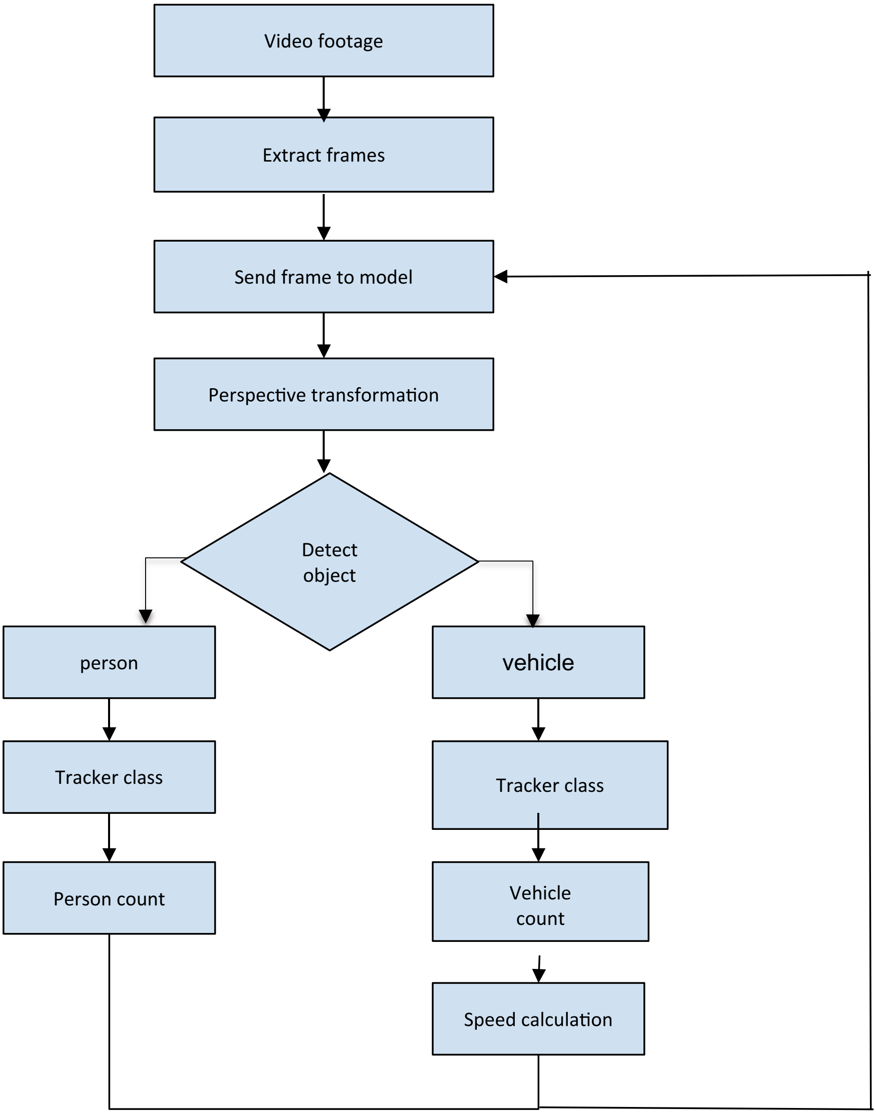

Video footage
Extract frames
Send frame to model
Perspective transformation
Detect object
person
vehicle
Tracker class
Tracker class
Person count
Vehicle count
Speed calculation

Fig. 2 Proposed system workflow

3.3 *Object Detection and Classification*

On our annotated dataset, first we trained a custom object detection model using the YOLOv9 model. We modified the model to fit our particular detection needs, so optimising its capacity to precisely identify cars and pedestrians in real-time. It looked over every frame of the input video upon deployment to identify any objects in the scene. These objects were arranged into the suitable groups (vehicle, bus, truck, motorbike, human, etc.), based on the confidence ratings and bounding box coordinates of the model. Redundant detections were eliminated and general detection accuracy was raised by means of NMS, so strengthening our detection system.

3.4 Counting Vehicles and Pedestrians

Our original counting system was developed to precisely count cars and pedestrians in real time in order to offer complete traffic flow analysis. Two horizontal lines were drawn in the video frame to indicate counting zones, and the algorithm was based on object trajectory analysis. An object was considered to be traveling upward when it crossed the bottom line and then the top line, and vice versa. We have the midline y_m, bottom line y_b, and top line y_t coordinates. The tracked objects are assigned direction(Ω) according to the sequence in which they cross the lines.

$$y_t < (y + \mu) \text{ and } y_t > (y - \mu) \rightarrow \Omega = 0 \tag{1}$$

$$y_b < (y + \mu) \text{ and } y_b > (y - \mu) \rightarrow \Omega = 1 \tag{2}$$

3.5 Estimating Vehicle Speed

Our system not only counts and detects objects, but it also makes real-time speed estimates for cars it detects. We tracked the vehicle enclosing bounding box centre coordinates over a sequence of frames using a frame-by–frame analytic approach. We computed the displacement of these central coordinates over time to determine the distance each vehicle covered. Subsequently, separating the computed distance by the interval between frames approximated speed. Thanks to our method, we could dynamically track changes in vehicle speed and precisely identify possible traffic violations including speeding.

$$\text{speed} = \alpha \times \frac{\sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}}{\lambda} \tag{3}$$

With α as the conversion constant and λ as the constant pixels per metre.

3.6 Vehicle Speed Detection

We incorporated an overspeed vehicle recognition method to greatly increase the capacity of our system to detect traffic violations. A set threshold speed was created to identify vehicles surpassing the legal speed limit or particular traffic scenario criteria. Every occurrence of one was counted one at a time; vehicles identified as overspeed vehicles were labeled as those which were detected moving faster than this limit. With this counting process, we were able to identify and quantify potential traffic violations, so providing vital data for law enforcement and traffic control.

3.7 Vehicle and Pedestrian Counting

This approach aims to classify objects in line with their vertical position inside a frame and movement direction. Defining parameters including the y-coordinate of the bounding box centre, reference lines, and sets, it tracks objects travelling in (Cu) and out (Cd). It first finds whether the y-coordinate of an object falls inside a given range around every reference line. If so, it sets a direction value () and identifies which reference line it falls inside. Setting to 0 indicates upward movement should the object lie close to the top reference line (y_t). Set to 1 to indicate downward movement should it be close to the bottom reference line (y_b). Lastly, it verifies the direction value if an object is within a range around the middle reference line (y_m). The object's ID is added to the set of items moving in (Cu) if Ω is equal to zero, and to the set of objects going out (Cd) if Ω is equal to one.

Algorithm

```
$y \leftarrow$ y-coordinate of the bounding box centre.
$\Omega \leftarrow$ direction value of the objects.
$C_u \leftarrow$ This is a set of IDs of objects moving in.
$C_d \leftarrow$ This is a set of IDs of objects moving out.
$y_t, y_b, y_m \leftarrow$ coordinates of reference lines
$\mu \leftarrow$ This is a constant value.
if $y_t < (y + \mu)$ and $y_t > (y - \mu)$ then
    $\Omega \leftarrow 0$
end if
if $y_b < (y + \mu)$ and $y_b > (y - \mu)$ then
    $\Omega \leftarrow 1$
end if
if $y_m < (y + \mu)$ and $y_m > (y - \mu)$
      if $\Omega \leftarrow 0$ then
      $C_u \leftarrow C_u + 1$
```

```
        elif $\Omega \leftarrow 1$ then
        $C_d \leftarrow C_d + 1$
        end if
    end if
```

3.8 Speed Calculation Algorithm

This algorithm iterates over a set of bounding boxes (bbox_id), extracting their coordinates and calculating the centroid. It then applies a perspective transformation (t_p) and extracts transformation coefficients (t_c). For each bounding box, if its ID exists in the object data, it calculates the time difference (t_d) between the current and previous time instances, along with the displacement (d) among the present location and the previous location. If the time difference is greater than or equal to 1, it computes the distance (d) travelled by the object, adjusts it based on a pixel-per-meter ratio (ppm), and calculates the speed (s) of the object.

Algorithm

```
    for bbox in bbox_id do
      $p_1$ , $q_1$ , $p_2$, $q_2$ $\leftarrow$ coordinates of bbox
      $c_x \leftarrow (p_1+p_2)/2$
      $c_y \leftarrow (q_1+ q_2)/2$
        $t_p \leftarrow$ perspectiveTransform(p)
        $t_c \leftarrow ( t_0, t_1 )$
        if id in object_data do
          ct $\leftarrow$ current time
          pt $\leftarrow$ previous time
          pp $\leftarrow$ previous position
          td $\leftarrow$ ct $-$ pt
          $k \leftarrow (t_0 - pp_0)^2 + (t_1 - pp_1)^2$
          if td >=1 do
            d$\leftarrow$sqrt(k)
          d $\leftarrow$ d /ppm
          s $\leftarrow$ d /td
          end if
        end if
    end for
```

4 Results and Discussions

All of the system's tests are conducted on a high-performance computing platform employing GPU acceleration on a real-time processing capability basis. The proposed system made use of several open-source libraries, such OpenCV for video processing and PyTorch for deep learning chores, and ran on the Python programming language.

4.1 Data Collection and Preparation

We focused on building a representative and varied dataset over this phase to appropriately train our object detection model. We positioned high-definition cameras at many intersections and pedestrian areas to capture a range of events, including changing lighting, weather, and traffic loads. This guaranteed that our model would fit actual conditions rather nicely. To maintain consistency and quality of data, we selected video for our dataset using strict criteria. Low degrees of occlusion, distortion, and motion blur were preferred to ensure exact annotations and consistent model training. We also meticulously labelled the dataset adding ground truth labels for cars and walkers. These annotations serve as effective benchmarks for training and evaluation of our object detection model. Over 15,000 samples from classes like vehicle, bus, truck, bicycle, motorbike, and person were used to train proposed model. The samples of the COCO [30] dataset are illustrated in Fig. 3.

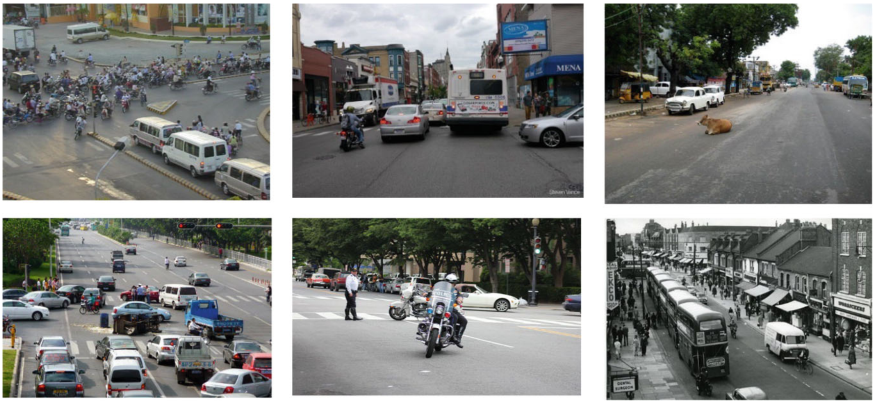
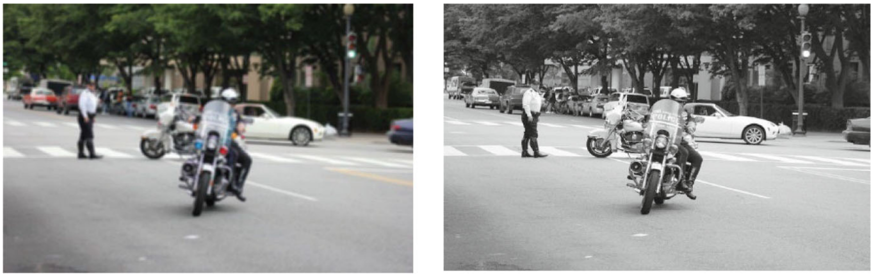


Fig. 3 Illustration of images in the COCO [30] dataset



(a) Before resize and noise reduction **(b)** After resize and noise reduction.

Fig. 4 Pre-processing. **a** Before resize and noise reduction, **b** after resize and noise reduction

4.2 Data Pre-processing

Several methods were used in this pre-processing step, such as noise reduction, normalization, and resizing. The images before and after pre-processing are shown in Fig. 4a, b.

4.3 Parameters Used to Train the Model

Table 2 provides an overview of the hyperparameters utilized for training the chosen model. The YOLO configuration specifies a batch size of 32, meaning that during each training iteration, 32 images are processed simultaneously. The learning rate is set to 0.001, regulating the step size for adjusting the model's weights and minimizing the loss function.

The training process spans 100 epochs, allowing the model to iterate through the entire dataset 100 times. The input images are resized to 416 × 416 pixels before being fed into the network, ensuring consistency in dimensions. To mitigate overfitting, a weight decay of 0.0005 is applied, which discourages excessively large weights. The momentum parameter is set to 0.937, helping to accelerate gradient updates and facilitate faster convergence. The Adam optimizer is selected due to its adaptive learning rate and efficiency in handling sparse gradients. These hyperparameters are carefully chosen to enhance model performance by maintaining an optimal balance between training speed, stability, and generalization.

Table 2 YOLOv9 training parameters

Batch size	Learning rate	epochs	Input size	Weight decay	Momentum	Optimizer
32	0.001	100	416 × 416	0.0005	0.937	adam

4.4 Evaluation Metrics

The performance of the proposed model is evaluated using several key metrics. The mathematical formulas for precision (Eq. 4), recall (Eq. 5), accuracy (Eq. 6), and mean Average Precision (mAP) (Eq. 7) are provided. Here, $P_t, P_f, N_t\ and\ N_f$ represent true positives, false positives, true negatives, and false negatives, respectively.

$$Precision = \frac{P_t}{P_t + P_f} \tag{4}$$

$$Recall = \frac{P_t}{P_t + N_f} \tag{5}$$

$$Accuracy = \frac{P_t + N_t}{P_t + N_t + P_f + N_f} \tag{6}$$

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{7}$$

4.5 Performance and Comparative Analysis

A carefully selected dataset of video footage from multiple surveillance cameras positioned at key points, such as intersections, pedestrian walkways, and city streets, served as the basis for our experiments. The dataset covered a range of possibilities including variations in traffic density, meteorology, and illumination conditions. Every video sequence was painstakingly annotated to provide ground truth labels for cars and people, so enabling supervised learning for tasks including object detection and tracking. The dataset included video from both stationary and dynamic camera viewpoints, so simulating real-world surveillance environments.

By guaranteeing that our system could generalize effectively to many environmental conditions and camera views, this variety enhanced the resilience and adaptability of our system in practical uses. The dataset also included cases of limited visibility, occlusions, and varying item scales, which made it challenging for our model to consistently find and follow objects in trying circumstances. To assess the efficiency of our surveillance system, we considered a broad spectrum of performance indicators catered to the particular objectives of every component. Using established criteria, we assessed the accuracy of object localisation and category prediction for object identification and classification. We also considered the mean Average Precision (mAP) for several item categories to evaluate general detection performance. Ground truth annotations were compared with object trajectory prediction and counting accuracy for the tracking and counting modules. The system's effectiveness in precisely tracking the movements of cars and pedestrians was measured using metrics like tracking precision, average tracking error, and counting accuracy. The values of these metrics—accuracy, precision, recall, and mAP are shown in Table 4.2. By contrasting the system's estimates with manually or with the aid of auxiliary monitoring systems observed ground truth speeds, the accuracy of the speed estimating process was assessed. The confusion matrix plot of our model's predicted labels over true labels is shown in Fig. 5 below. People and vehicles, including cars, buses, trucks, and motorcycles, are included in the labeling. The charts for the metrics accuracy, precision, recall, mAP, box_loss, cls_loss, and obj_loss for both are shown in Fig. 6.

Table 3 presents a comparison of the performance of various object detection models, including YOLOv3, YOLOv4, SSD, and the proposed model. The results show significant advancements in accuracy, mean Average Precision (mAP), precision, and recall. YOLOv3 achieves a balanced performance with an accuracy of 0.576, mAP of 76.52, precision of 78.84, and recall of 74.20, making it a robust model but not the top performer. YOLOv4 outperforms YOLOv3 with an accuracy of 0.728 and precision of 81.50, although its mAP of 74.2 and recall of 77.00 indicate better object identification but slightly less precision in localization. The SSD model, with an accuracy of 0.485, mAP of 61.29, precision of 69.78, and recall of 62.00, lags, struggling with both detection and localization. Our model, on the other hand,

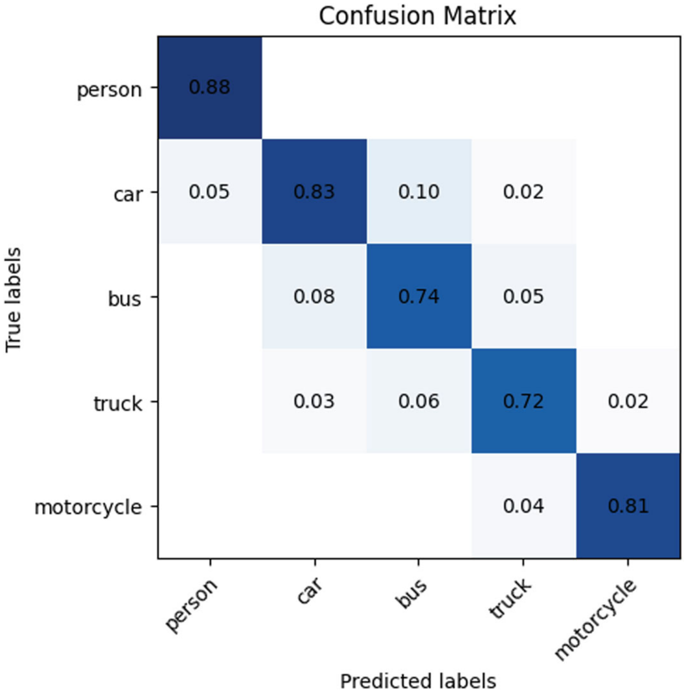


Fig. 5 Confusion matrix for the model

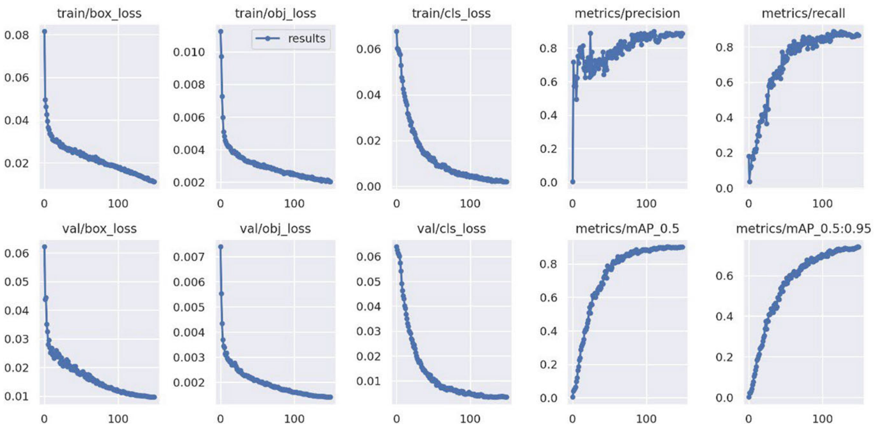


Fig. 6 Precision and recall curves

Table 3 Comparison of the proposed model with existing models

Models	Precision	Recall	Accuracy	mAP
YOLOv3	78.84	74.20	0.576	76.52
YOLOv4	81.50	77.00	0.728	74.2
SSD	69.78	62.10	0.485	61.29
Our model	**89.45**	**88.00**	**0.914**	**85.15**

performs noticeably better than all of these models, with a remarkable accuracy of 0.914, mAP of 85.15, precision of 89.45, and recall of 88.00. These measures show the better item detection and localization capacity of our model. Because of its great precision and recall values, which show a balanced approach that reduces both false positives and false negatives, it is quite successful for difficult object detection tasks.

4.6 Analysis of Surveillance System Results

The results of our surveillance system revealed great performance in a spectrum of operational conditions and environmental surroundings. Real-time monitoring of vehicle and pedestrian traffic made accurate counting, tracking, and speed estimate possible as well as provided valuable data for traffic management and urban planning. Machine learning algorithms especially the YOLOv9 model enhanced accuracy and dependability in item detection and classification tasks even in dynamic settings with complex backgrounds and occlusions. The proposed method routinely performed well in real-world applications in precisely identifying and tracking vehicles and pedestrians in a range of environmental conditions and camera angles. The custom counting technique effectively counted the in- and out-of-pocket motions of vehicles and pedestrians, so enabling complete traffic flow monitoring and congestion control. Estimating speed helped law enforcement identify vehicles running above the speed limit, so enhancing traffic safety and ease of spotting violations.

All things considered, the results of the analysis of the surveillance system revealed how well it performs in pragmatic environments, providing stakeholders with pertinent data for planning urban infrastructure, enhancing safety, and streamlining traffic. Constant monitoring and parameter and algorithm optimization of the system will help to further enhance its performance and capacity to adapt to changing traffic conditions and technology developments.

Figure 7 displays the output of the model on Vignan University's gate video, produced from CCTV footage of the gate. Figure 8 shows the model's output on CCTV footage of a crowded path with changing lighting conditions. The model is rather good at detecting even at night.

5 Conclusions and Future Scope

This chapter demonstrates the YOLOv9 model's performance for vehicle and human counting as well as speed estimates employing distance computations. Using state-of-the-art computer vision technologies, a real-time system for item detection, counting, and speed prediction has been developed showing promise in urban planning, traffic control, and public safety. The YOLOv9 model has been crucial in precisely identifying and tracking cars and pedestrians, so enabling effective counting and estimate of speed. Distance-based speed estimate has helped us to better understand traffic dynamics and behaviours by offering perceptive data on item movement patterns. The outcomes have significant consequences for public safety campaigns, intelligent transportation systems, traffic control mechanisms, and environmental impact studies. Using the most recent YOLO models and innovative distance estimate approaches, we have laid the foundation for forthcoming advancements in computer vision, machine learning, and transportation systems. Emphasizing system scalability and resilience, future research could look at uses in retail analytics, environmental monitoring, and smart city projects. By means of enhanced vehicle and human counting and speed estimation, the development of intelligent transport systems can help to support the construction of more sustainable and efficient metropolitan environments.

This chapter shows the revolutionary possibilities of modern technologies including computer vision and machine learning in addressing challenging issues in public safety and traffic control. It highlights how innovation will influence how transportation networks develop in the future. The suggested monitoring system is an innovative attempt to manage urban traffic using cutting-edge technologies. We have created a scalable method to improve urban traffic flow by fusing computer vision, machine learning, and real-time data analytics. We hope to increase the system's

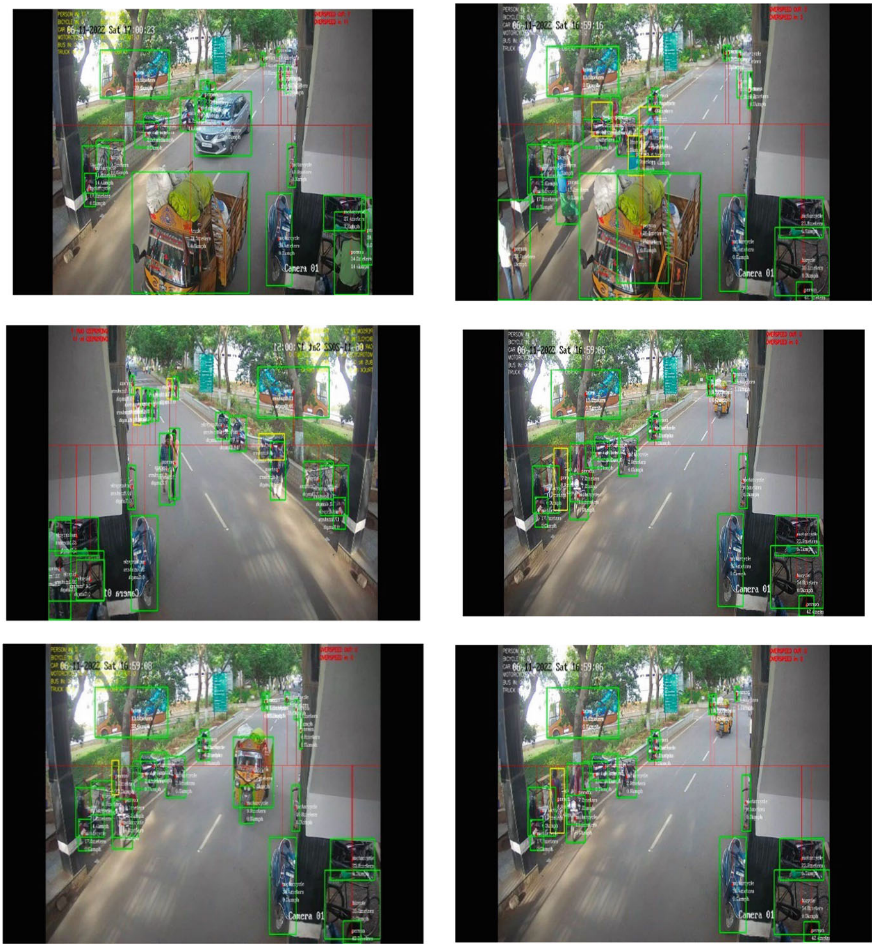


Fig. 7 Model findings on the Vadlamudi admission gate video of Vignan University

influence and help create safer, more sustainable cities through continued research and cooperation.

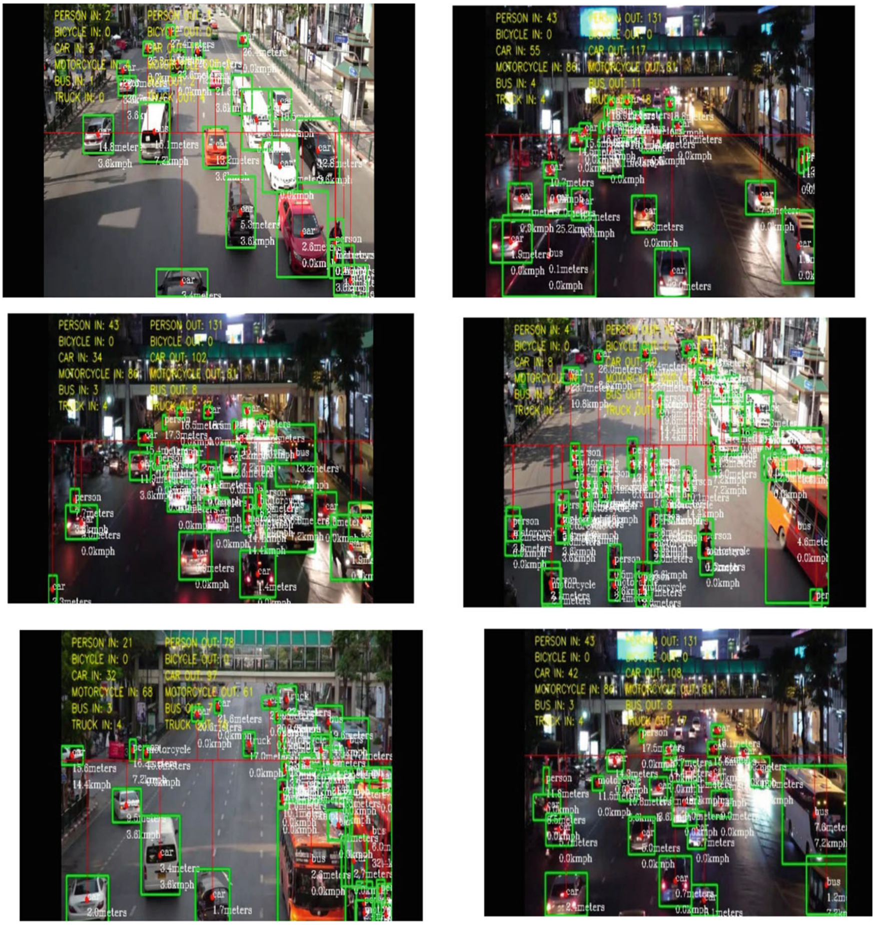

PERSON IN: 2
BICYCLE IN: 0
CAR IN: 3
BUS IN: 1
TRUCK IN: 0
PERSON IN: 43
BICYCLE IN: 0
CAR IN: 55
MOTORCYCLE IN: 86
BUS IN: 4
CAR OUT: 117
BUS OUT: 11
PERSON IN: 43
BICYCLE IN: 0
CAR IN: 34
MOTORCYCLE IN: 86
BUS IN: 3
PERSON OUT: 131
CAR OUT: 102
BUS OUT: 8
PERSON IN: 4
BICYCLE IN: 0
CAR IN: 8
PERSON IN: 21
BICYCLE IN: 0
CAR IN: 32
MOTORCYCLE IN: 68
BUS IN: 3
TRUCK IN: 4
PERSON OUT: 78
CAR OUT: 37
MOTORCYCLE OUT: 61
PERSON IN: 43
BICYCLE IN: 0
CAR IN: 42
MOTORCYCLE IN: 86
BUS IN: 3
PERSON OUT: 131
CAR OUT: 108
BUS OUT: 8

Fig. 8 Model output on a busy road's CCTV footage

References

1. Harshitha, R., Manikandan, J.: Design of a real-time pedestrian detection system for autonomous vehicles. In: 2017 IEEE Region 10 Symposium (TENSYMP), pp. 1–4. IEEE (2017, July)
2. Wang, K., Fang, B., Qian, J., Yang, S., Zhou, X., Zhou, J.: Perspective transformation data augmentation for object detection. IEEE Access **8**, 4935–4943 (2019)
3. Zhang, J., Zhang, J., Chen, B., Gao, J., Ji, S., Zhang, X., Wang, Z.: A perspective transformation method based on computer vision. In: 2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), pp. 765–768. IEEE (2020, June)
4. Wu, B.F., Lin, C.T.: Robust image measurement and analysis based on perspective transformations. In: 2006 IEEE International Conference on Systems, Man and Cybernetics, vol. 3, pp. 2390–2395. IEEE (2006, October)

5. Perafan-Villota, J.C., Mondragon, O.H., Mayor-Toro, W.M.: Fast and precise: parallel processing of vehicle traffic videos using big data analytics. IEEE Trans. Intell. Transp. Syst. **23**(8), 12064–12073 (2021)
6. Dai, Z., Song, H., Wang, X., Fang, Y., Yun, X., Zhang, Z., Li, H.: Video-based vehicle counting framework. IEEE Access **7**, 64460–64470 (2019)
7. Shami, M.B., Maqbool, S., Sajid, H., Ayaz, Y., Cheung, S.C.S.: People counting in dense crowd images using sparse head detections. IEEE Trans. Circuits Syst. Video Technol. **29**(9), 2627–2636 (2018)
8. Yang, H., Zhang, Y., Zhang, Y., Meng, H., Li, S., Dai, X.: A fast vehicle counting and traffic volume estimation method based on convolutional neural network. IEEE Access **9**, 150522–150531 (2021)
9. Liu, C., Huynh, D.Q., Sun, Y., Reynolds, M., Atkinson, S.: A vision-based pipeline for vehicle counting, speed estimation, and classification. IEEE Trans. Intell. Transp. Syst. **22**(12), 7547–7560 (2020)
10. Xiang, X., Zhai, M., Lv, N., El Saddik, A.: Vehicle counting based on vehicle detection and tracking from aerial videos. Sensors **18**(8), 2560 (2018)
11. Lin, C.J., Jeng, S.Y., Lioa, H.W.: A real-time vehicle counting, speed estimation, and classification system based on virtual detection zone and YOLO. Math. Probl. Eng. **2021**(1), 1577614 (2021)
12. Lin, C.J., Jhang, J.Y.: Intelligent traffic-monitoring system based on YOLO and convolutional fuzzy neural networks. IEEE Access **10**, 14120–14133 (2022)
13. Sambolek, S., Ivasic-Kos, M.: Automatic person detection in search and rescue operations using deep CNN detectors. IEEE Access **9**, 37905–37922 (2021)
14. Pang, C.C.C., Lam, W.W.L., Yung, N.H.C.: A method for vehicle count in the presence of multiple-vehicle occlusions in traffic images. IEEE Trans. Intell. Transp. Syst. **8**(3), 441–459 (2007)
15. Tayara, H., Soo, K.G., Chong, K.T.: Vehicle detection and counting in high-resolution aerial images using convolutional regression neural network. IEEE Access **6**, 2220–2230 (2017)
16. Moranduzzo, T., Melgani, F.: Automatic car counting method for unmanned aerial vehicle images. IEEE Trans. Geosci. Remote Sens. **52**(3), 1635–1647 (2013)
17. Unzueta, L., Nieto, M., Cortés, A., Barandiaran, J., Otaegui, O., Sánchez, P.: Adaptive multicue background subtraction for robust vehicle counting and classification. IEEE Trans. Intell. Transp. Syst. **13**(2), 527–540 (2011)
18. Khel, M.H.K., Kadir, K.A., Khan, S., Noor, M., Nasir, H., Waqas, N., Khan, A.: Realtime crowd monitoring—estimating count, speed and direction of people using hybridized YOLOv4. IEEE Access **11**, 56368–56379 (2023)
19. Zarei, N., Moallem, P., Shams, M.: Fast-Yolo-rec: incorporating Yolo-base detection and recurrent-base prediction networks for fast vehicle detection in consecutive images. IEEE Access **10**, 120592–120605 (2022)
20. Li, S., Liu, C., Chang, F.: Time-spatial multiscale net for vehicle counting and traffic volume estimation. IEEE Trans. Cogn. Dev. Syst. **14**(2), 740–751 (2021)
21. Tsai, C.M., Shih, F.Y., Hsieh, J.W.: Real-time vehicle counting by deep-learning networks. In: 2022 International Conference on Machine Learning and Cybernetics (ICMLC), pp. 175–181. IEEE (2022, September)
22. Al-Ariny, Z., Abdelwahab, M.A., Fakhry, M., Hasaneen, E.S.: An efficient vehicle counting method using mask R-CNN. In: 2020 International Conference on Innovative Trends in Communication and Computer Engineering (ITCE), pp. 232–237. IEEE (2020, February)
23. Vijayalakshmi, M., Suvitha, D., Krishna, C.G.: Moving vehicle speed and distance estimation in autonomous vehicles. In 2023 12th International Conference on Advanced Computing (ICoAC), pp. 1–5. IEEE (2023, August)
24. Ahmad, M., Ahmed, I., Adnan, A.: Overhead view person detection using YOLO. In 2019 IEEE 10th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON), pp. 0627–0633. IEEE (2019, October)

25. Saxena, G., Paraye, A., Verma, D.K., Rajan, A., Verma, R.K.: Deep Learning–Based Vehicle Counting and Speed Estimation in Surveillance Videos Using Object Detection. Available at SSRN 4573959
26. Fang, W., Wang, L., Ren, P.: Tinier-YOLO: a real-time object detection method for constrained environments. IEEE Access **8**, 1935–1944 (2019)
27. Wanye, Y., Jinping, L.: Pedestrian detection algorithm based on improved Faster R-CNN. Sci. Technol. Eng. **20**(4), 1498–1503 (2020)
28. Satti, S.K., SD, K., SP.: R-ICTS: recognize the Indian cautionary traffic signs in real-time using an optimized adaptive boosting cascade classifier and a convolutional neural network. Concurrency Comput.: Pract. Experience (2022)
29. Satti, S.K., Rajareddy, G.N.V., Maddula, P., Vishnumurthy Ravipati, N.V.: Image caption generation using ResNET-50 and LSTM. In: 2023 IEEE Silchar Subsection Conference (SILCON), Silchar, India, pp. 1–6. (2023)
30. Lin, T.Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., et al.: Microsoft coco: common objects in context. In: Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6–12, 2014, Proceedings, Part V 13, pp. 740–755. Springer International Publishing (2014)

Accident Detection from CCTV Surveillance Using Hybrid Vision Transformation and Alert the Nearest Hospital

Md Oqail Ahmad and Shams Tabrez Siddiqui

Abstract Accident detection in real-time is critical to ensuring prompt medical assistance and minimizing casualties. Accidents remain a leading cause of death in India. More than 80% of the victims die due to late aid received by them instead of the accident itself. In case of an accident, the victims are not given any early medical attention, especially on highways with high volumes of fast-moving traffic. This paper presents a new approach to accident identification from CCTV surveillance using a hybrid vision transformation framework combined with an automated alert system for notifying the nearest hospital. A system is proposed that would use a hybrid vision transformer for processing real-time footage from CCTV cameras that detect accidents. This proposed model has been suggested using vision transformers with CNNs to enhance efficiency and accuracy in the detection of accidents. The prevalent method for image classification is using CNNs, which are much faster and more accurate than all other techniques. It saves time in medical response by improving the process of accident detection via advanced image processing techniques. The implementation of such a system could make a fundamental difference in road safety and save lives. The system is designed to operate efficiently in diverse environments, such as highways, urban roads, and parking areas, demonstrating high accuracy and scalability.

Keywords CCTV surveillance · Accident detection · Hybrid vision transformer · CNN

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1 Introduction

Every year, 1.3 million people are killed and another 25–65 million people suffer minor injuries in automobile accidents [1]. Most of this problem is found in the poor and nations with miiddle income, sometimes referred to as developing countries, which also boast the highest rate of deaths from traffic accidents. In comparison to the high-income or developing countries, with a rate of 11.3 deaths per 100,000 people, the rate of road traffic deaths in the industrialized countries is about 23.5 deaths per 100,000 people [2]. It is a shocking fact that more than 90% of traffic fatalities occur in underdeveloped nations, yet they only have half the number of automobiles in the world. According to statistics, 13 people die in India every hour in accidents. However, as the real figures are not reported, they may be lower. With an estimated 140,000 road deaths per year, India is now projected to be the country with the most road deaths.

Most accidents happen in three stages: the second phase, which is the deadliest and accounts for 75% of all deaths, happens within one hour of the accident. Swift action can be minimized in this circumstance, and the victims' urgent need for support can be addressed. We aim to use a machine that can quickly analyze the situation by reading the video that has been taken by the camera. By thinking about the situation and alerting the authorities, the system is an important tool to help the victims. The goal is to use centralized networks (CNN or ConvNet) [3].

1.1 Role of DL and CNNs in Detection of Road Accidents

The background review delves into the global landscape of road accidents, emphasizing the pressing issue of fatalities and injuries associated with traffic incidents. With over 1.3 million deaths annually and millions suffering mild to severe injuries, the toll on human life and wellbeing is significant. According to the World Health Organization report[4], the number of traffic accidents in developed nations or high-income and low-income or underdeveloped nations differs significantly. Developing nations, despite having only half of the world's vehicles, bear more than 90% of road traffic-related deaths [2]. The review underscores the need for targeted interventions in these regions to address the challenges posed by inadequate emergency response systems and suboptimal road safety measures. 3 Furthermore, the review underscores the critical importance of the time factor in the aftermath of accidents. The three phases of an accident, particularly the second phase within an hour, carry the highest mortality rate. This period presents a window of opportunity for intervention, and the proposed project aims to leverage advanced Algorithm for Deep Learning, particularly Convolutional Neural Networks (CNNs) [5], to detect accidents within seconds. The focus is on highways, where the traffic density is lower, and timely assistance is often lacking. Intelligent Transportation Systems (ITS) are acknowledged as promising tools to enhance transportation safety and control. The review lays the groundwork for the project by recognizing the need for innovative solutions that integrate technology, machine learning, and real-time video datasets tofor tranning model to improve emergency response times and overall road safety [6].

1.2 The Problem Statement

The problem addressed in this project is the persistently high rate of road accidents, resulting in a staggering number of deaths and injuries globally, with a particular focus on the situation in developing countries. The World Health Organization's survey underscores the severity of the issue, revealing that over 1.3 million people succumb to road accidents each year, while an additional 25–65 million suffer mild injuries [1]. The disparities between nations with low and moderate incomes, such as developing countries, as well as developed or high income nations are stark, with the former experiencing a significantly higher road accident death rate of 23.5 per 100,000 population compared to the latter's 11.3 per 100,000. Moreover, the prevalence of road traffic-related deaths in developing countries exceeds 90%, despite accounting for only half of the world's total vehicles. In India, the situation is particularly dire, with an average of 13 people losing their lives every hour due to road accidents, a statistic that could be underestimated as many cases go unreported. The second phase of an accident, occurring within an hour, emerges as a critical period with the highest mortality rate, constituting 75% of all deaths. The inadequacy of timely help reaching accident victims during this phase is a key concern, leading to preventable fatalities. This work seeks to address this specific problem by proposing the implementation of advanced Algorithm for Deep Learning, specifically Convolutional Neural Networks (CNNs) [3], to detect accidents within seconds of their occurrence. Focusing on highways, where traffic density is lower and timely assistance is often lacking, the project aims to deploy CCTV cameras approximately 500 m apart. These cameras will serve as a surveillance medium, capturing real-time video footage 4 for analysis by the proposed accident detection model.

1.3 Contribution

- The paper introduces a new hybrid vision transformer model that combines both vision transformers and convolutional neural networks. It substantial increases the precision of accident detection with the help of global contextual awareness and local spatial information.
- Proactive alerting system, when the likelihood of accidents increases above a certain level, it activates the proactive alerting system, which sends SMS notifications to the nearest hospital. This ensures that the emergency response is prompt, that is, the intervention time reduction may save lives.

- Integration with Hospital Databases the technology alerts the nearest appropriate medical facility by smoothingly integrating with the hospital databases. In the case of densely populated urban areas where the trends of traffic patterns and distance to the medical facilities have their impact on emergency response, this integration helps in allocating the resources and, thereby, reduces the response time.
- The research proposes an effective system for accident detection through CCTV monitoring, thus ensuring better safety for the public. The technology enables timely intervention due to the integration of state-of-the-art AI algorithms with real-time observation, which may help in reducing the impact of accidents on individuals and communities.

The remaining section of the paper is arranged as follows: recognizes the gaps in resaerch pertaining to our research in Sect. 2. Section 3 is separated into two portions Sect. 3.1. the proposed model is described. The algorithm of the hybrid vision transformer model is discussed based on the proposal to increase the accuracy, recall, F1-score, and minimize CrossEntropyLoss in Sect. 3.2. Section 4 parameters estimation, results, and conclusion and future work are covered in Sect. 5, after evaluation of the proposed work has been presented and discussed.

2 Related Work

Twitter sentiment analysis using NLTK and Transformers leverage natural language processing techniques to categorize sentiments expressed in tweets. Researchers have investigated sentiment analysis in numerous contexts, including the COVID-19 pandemic [2, 4]. Determining if tweets express neutral, positive, or negative feelings is part of this process [2]. Methods like deep learning and machine learning, which include CNNs (convolutional neural networks), have been employed for this purpose [5, 7]. Sentiment analysis tools like VADER and BERT have also been utilized to analyze sentiments in social media posts, including tweets [8–10].

The latest research is to see how various methods especially those using computer vision and deep learning in CCTV monitoring systems identify traffic accidents and trigger emergency services.

Basheer et al. [2] have preesnted a computer vision-based system that works in real time to detect and classify traffic events. The system uses big data analytics to fine-tune the accuracy of incident classification and reaction mechanisms. Their system provides emergency responders with the most recent information on incidents by analyzing incident trends and traffic patterns. The Alex Darknet, real-time traffic monitoring with a hybrid CNN architecture, was proposed. This model offers a robust foundation for accident detection through the integration of deep learning modules to achieve previously unseen reliability in traffic situation analysis.

Choi et al. [3] have used an ensemble of deep learning models that analyze multi-modal data from dashboard cameras to detect car crashes effectively. By integrating data from a few sensors, it can recognize accident scenarios with high accuracy, so emergency services can respond and assist more quickly. Integrating the Calogero-Moser system into CCTV, Lee et al. [5] has proposed a novel way of detecting highway accidents. This was followed by the early use of the integration of mathematical models with surveillance technology, leading to the development of more advanced accident detection systems.

Khan et al. [8] deep learning technique in practice to identify abnormalities in traffic patterns by analyzing video from CCTV. According to their technology, this system recognizes traffic behavior that deviates from the norm, indicating probable collisions and notifying the appropriate emergency agencies. Hooda et al. [9] developed an accident detection system using surveillance cameras that keep watchful eyes out for specific visual cues that indicate accidents. The technology notifies emergency services immediately after detection, which can pave the way for a timely deployment to the scene of an accident.

The approach of detecting real-time traffic accidents by using monitoring trajectory was provided by Zhang and Sung, [10]. Their method uses spatiotemporal data to detect sudden vehicle movements, which are usually observed before a collision. In their work, Ghahremannezhad et al. [11] showed how the system can be tuned for various lighting and environmental conditions using deep learning algorithms to process real-time data from CCTV for accident identification.

Ijjina et al. [12] developed a system which makes use of complex computer vision algorithms for the detection of abrupt changes in vehicle trajectories. This technology ensures that incidents are detected quickly and that emergency services are phoned immediately. For the detection and categorization of traffic accidents, Thakare et al. [13] employed deep learning in analyzing object interactions in traffic video recordings. The depth of this research considerably aids in quick responses to emergency services since it assists in determining the exact location and type of accidents.

A real-time notification mechanism of an AI-improved CCTV system that identifies road obstructions and vehicle accidents was developed by Lee et al. [5]. It is absolutely necessary to implement this kind of real-time notification mechanism to improve traffic safety and fast-track emergency response. Using video analytics, Tahir et al. developed a real-time, event-based traffic monitoring system. The accuracy along with the speed of the identification of accidents and alerting adjacent emergency services are enhanced by this approach.

Researched convolutional neural networks [14] as a possible tool for detecting and locating traffic incidents from the surveillance data. Their method helps emergency crews respond faster and more effectively because of the accurate and rapid interpretation of complex video patterns that are indicative of accidents.

These different techniques demonstrate the tremendous efforts in artificial intelligence [15], and computer vision technologies are being used to improve the accuracy, effectiveness, and speed of systems designed to detect traffic incidents and manage emergency responses.

Computer vision and deep learning are the most commonly studied topics in CCTV surveillance systems for emergency response and traffic accident detection. Techniques used are big data analytics for real-time incident classification; hybrid

CNN architectures for traffic monitoring; ensemble deep learning models for crash detection from dashboard cameras; mathematical model integration with CCTV for highway accident detection; trajectory tracking; anomaly detection in traffic patterns; and object interaction analysis in traffic videos [16]. Methods used are aimed at increasing responsiveness, accuracy, and efficiency of accident detection systems to increase traffic safety and establish a timely connection with the emergency services.

3 Proposed Methodology

3.1 Accident Detection from CCTV Surveillance Using Hybrid Vision Transformer Model

Accident Detection from CCTV Footage dataset from Kaggle was used to train the model [6]. The dataset contains thousands of labeled video clips, making it suitable for supervised learning. The video frames are first captured by the CCTV [17] surveillance system, as shown in Fig. 1, and then converted into individual frames. The input data for the hybrid vision transformer model is these frames. This model is the newest method for image classification due to the combination of Vision Transformers with Convolutional Neural Networks (CNNs) [15, 18]. CNNs are great at identifying spatial information in images, but Vision Transformers use their capability to use self-attention mechanisms to identify the context globally. Combining these two architectures gives the model the capability to analyze local as well as global data in each frame, thus increasing its accident detection accuracy.

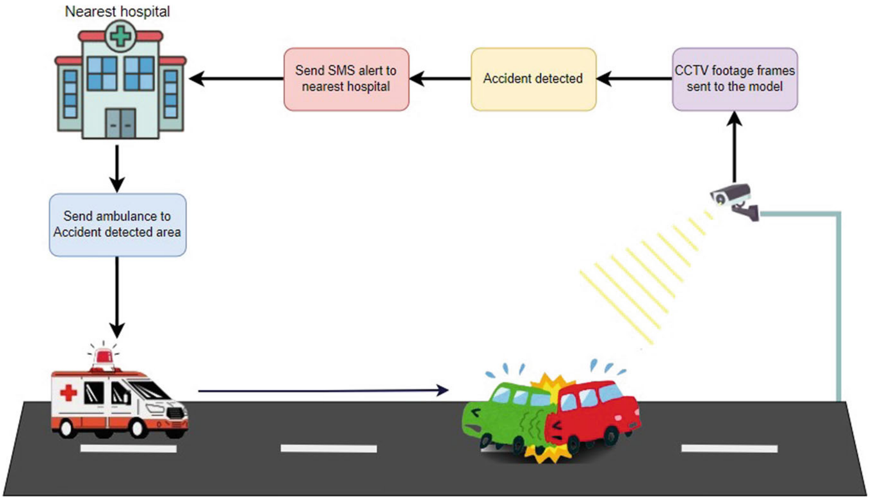
Nearest hospital
Send SMS alert to nearest hospital
Accident detected
CCTV footage frames sent to the model
Send ambulance to Accident detected area

Fig. 1 Real-time workflow of an automated emergency response system

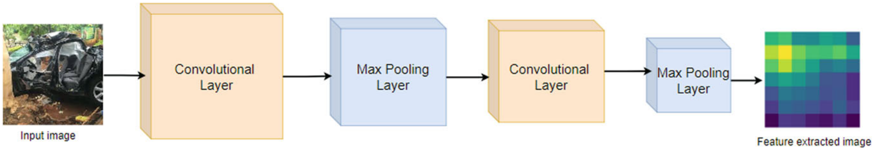

Fig. 2 Convolutional layers for feature detection and pooling layers for dimension reduction

The hybrid vision transformer model produces score that are indicative of the probability of an accident happening when each frame is estimated. The system sends a message alert to the closeby hospital if the accident score shoots above a certain threshold, usually set at 50%. This message contains all relevant details about the scene of the accident that were garnered from the memory of CCTV, storing information about the hospitals surrounding it. This proactive nature ensures that emergency responders are informed as early as possible, enabling them to start a quick reaction [17].

The ability of the system to utilize both local and global contextual information for the identification of accidents is an essential feature of its effectiveness. Traditional methods often focus solely on local features that the CNNs extract, as depicted in Fig. 2, which may cause the missing of important contextual details that exist in the broader scene. The hybrid model gains a more holistic understanding of each frame by integrating Vision Transformers, which are exceptional at identifying global dependencies. This, therefore, enhances the hybrid model's ability to identify accidents.

The direct connection of the system to hospital databases, furthermore, forwards the alerts to the most convenient fitting facility and improves maximum reaction times and efficient resource allocation. Resource allocation is mainly important in most metropolitan regions, where traffic and its trends as well as distance to medical centers affect response times.

A hybrid vision transformer methodology for accident detection from CCTV monitoring presents a number of methods to improve public safety. İn Fig. 1. show the workflow of our project in real-time, an automated emergency response system activated upon detecting a car accident through CCTV footage.

The system contains strong accident detection capabilities with the help of both CNNs and Vision Transformers, so lives are saved through timely intervention. Proactive alerting mechanisms in the system and a smooth interface with the hospital database make it possible for emergency services to act within a short time and lessen the effect of accidents on the targeted persons and communities.

A CNN can be considered a class of multi-layer neural networks that are extensively used for many classification of images based on activities due to their aptitude to effectively capture spatial hierarchies in images using the application of convolutional filters. Before sending input images to the patch layer of the vision transformer and other layers, the CNN layer is essential in your hybrid vision transformer model for accident detection from CCTV surveillance. It does this by extracting pertinent features from the images.

Convolutional layer: The convolutional layer is the foundation of a CNN. It takes a set of learned filters, or kernels, that are applied to the input image, giving rise to feature maps. Every filter in this set detects a specific pattern or feature of the input image. The presence of these features is represented in the output feature map at different spatial positions.

The formula for output feature map size:

$$\mathrm{O} = \frac{\mathrm{W} - \mathrm{F} + 2\mathrm{P}}{\mathrm{S}} + 1 \tag{1}$$

where:

O denotes size of the output.
W is dimension of input.
F represents filter's breadth or height.
P denotes the padding shape.
S denotes the stride.

Pooling Layer: The convolutional layers produce the feature maps. To save lots of information due to storage space and simultaneously reduce the amount of the spatial dimentions of the feature maps, the feature maps obtained from the convolutional layers are reduce in size using pooling layers. The two common pooling methods are maximum pooling and average pooling.

The formula for output size after pooling:

$$\mathrm{O} = \frac{\mathrm{W} - \mathrm{F}}{\mathrm{S}} + 1 \tag{2}$$

The final image is sent to later layers in the vision transformer architecture after CNN layers extract features from CCTV surveillance footage for accident detection. This integration aims to leverage CNNs and transformers' respective advantages in picture comprehension challenges. Figure 2. describe that CNNs use convolutional layers with filters to detect features in images, which are then down-sampled by pooling layers to reduce dimensions.

Patch Layer: The image is separated into more manageable, smaller patches once it has been feature-extracted from the CNN layers. Every patch denotes a specific area inside the input image. We create 49 patches in our model by dividing the image into a grid of 7 × 7 patches as represented in Fig. 3. By doing this step, parallel processing is made easier and the transformer may focus on local information inside the image.

Patch Embedding Layer: A learnable linear transformation is used to project each patch into a lower-dimensional embedding space once the image has been divided into patches.

Through this method, each patch is transformed into a fixed-size embedding vector using Eq. (3), allowing the transformer layers to process it further.

The formula for patch embedding can be represented as:

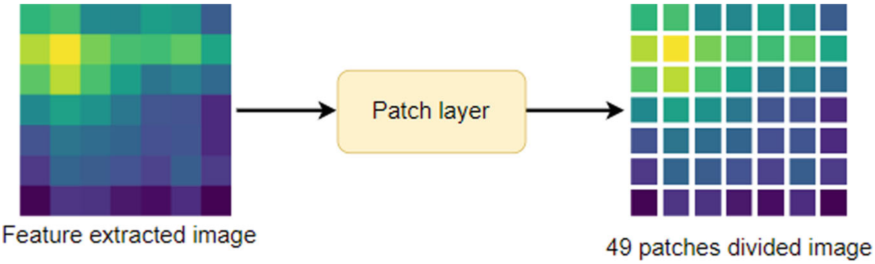

Fig. 3 Image is divided into a grid, creating patches for parallel processing and localized focus in transformers

$$\mathrm{X_{patch}} = \mathrm{X_{image}} \times \mathrm{W_{patch}} + \mathrm{b_{patch}} \tag{3}$$

where:

$\mathrm{X_{image}}$	is the input image.
$\mathrm{W_{patch}}$	is the weight matrix for patch embedding.
$\mathrm{b_{patch}}$	is the bias term.

Positional Embedding Layer: Understanding spatial relationships in vision transformers requires knowing the position of each patch in the image, as contrast to sequential data where this information is implicit. Positional information is obtained by appending positional embeddings to the patch embeddings. Using sinusoidal functions or positional encodings in Eq. (4) that have been learned is a popular strategy. the embedding in place formula can be expressed as:

$$\mathrm{PE_{(pos,2i+1)}} = \cos\left(\mathrm{pos}/1000^{2i/d_{model}}\right) \tag{4}$$

where:

pos	is the position.
i	is the dimension index.
$\mathrm{d_{model}}$	is the dimension of the model.

Transformer Encoder Layer: The transformer encoder layers are the central component of the visual transformer design. Each encoder layer is made up feed-forward neural network sub-layers and muli-head self-attension. The model can capture both local and global dependencies by focusing on distinct segments of the input sequence at the same time thanks to multi-head attention given as Eq. (4). Effective information fusion between various regions of the image is made possible by a weighted summation of each patch's representation that occurs after the attention process, which is dependent on the attention scores using Eq. (5). The model as represented in Fig. 4 is able to collect a variety of features of the input image by repeating this procedure across many attention heads. Every feedforward neural network, that is to say, every transformer block acts upon the result of the multi-head attention mechanism to further process and improve features. The FFN consists of two linear layers, divided by an activation function that is not linear, usually a ReLU or GELU.

$$\mathrm{Attention}(\mathrm{Q},\mathrm{K},\mathrm{V}) = \mathrm{softmax}\left(\frac{\mathrm{Q}\cdot\mathrm{K}^{\mathrm{T}}}{\sqrt{\mathrm{d_k}}}\right)\mathrm{V} \tag{5}$$

$$\mathrm{MulitiHead}(\mathrm{Q},\mathrm{K},\mathrm{V}) = \mathrm{Concat}(\mathrm{head}_1,\ \ldots,\ \mathrm{head}_h)\mathrm{W}^0 \tag{6}$$

$$\mathrm{head_i} = \mathrm{Attention}\left(\mathrm{QW_i^Q},\mathrm{KW_i^K},\mathrm{VW_i^V}\right) \tag{7}$$

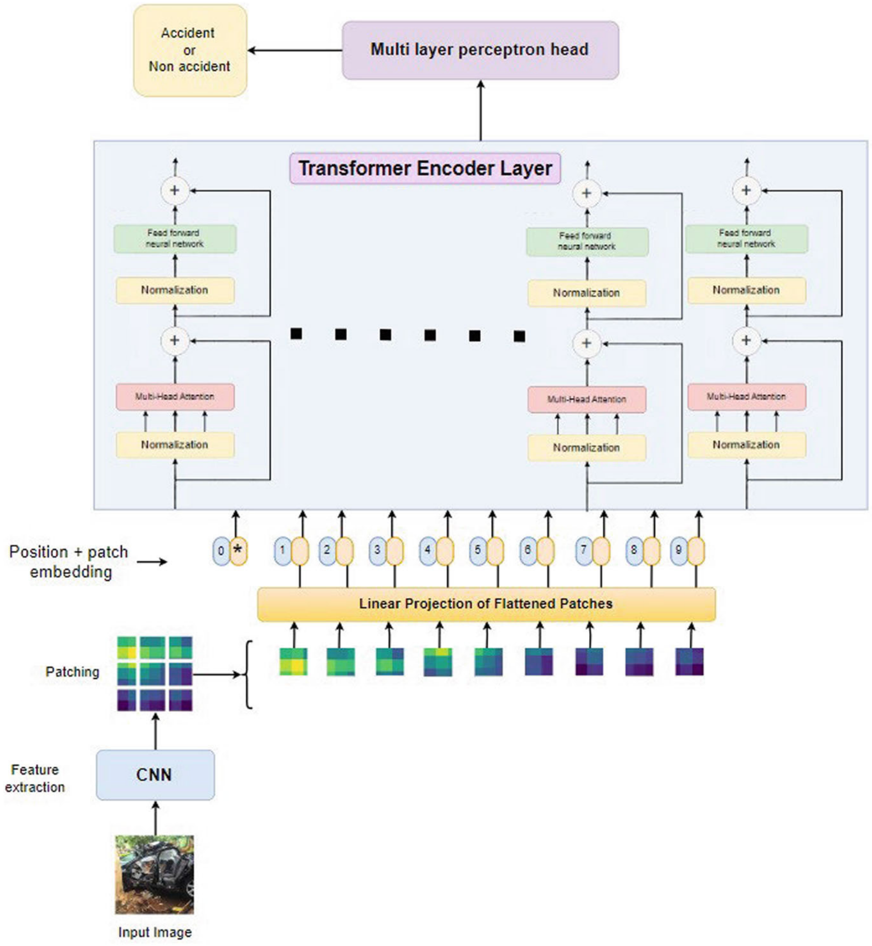
Accident
or
Non accident
Multi layer perceptron head
Transformer Encoder Layer
Feed forward neural network
Normalization
Multi-Head Attention
Normalization
Position + patch embedding
0
*
1
2
3
4
5
6
7
8
9
Linear Projection of Flattened Patches
Patching
Feature extraction
CNN
Input Image

Fig. 4 Proposed hybrid vision transformer architecture

where:

The queries keys, and values are denoted by Q, K, and V respectively.

W_i^Q, W_i^K, W_i^V, and W^0	are the weight matrices for linear transformations.
d_k	denotes the dimensionality of the key vectors.
h	is the number of attention heads.

The Hybrid Vision Transformer architecture as represented in Fig. 4 efficiently captures both local and global spatial information by hierarchically combining CNN, patch embedding, positional embedding, multi-head attention, and FFNs. With tasks like accident detection from CCTV monitoring, where contextual understanding is essential for precise film analysis, this architecture makes it perfect.

3.2 *Proposed Hybrid Model Algorithm*

The algorithm inputs batched image data, applies a CNN to extract features, and divides images into P × P patches. Positional encodings are added to patch embeddings. For L layers, it performs self-attention, applying softmax for attention weights, and then computes the attention output. It transforms attention to output, adds residuals, and normalizes. It follows with two linear transformations, an activation function, another residual connection, and normalization. After looping through layers, it aggregates the patch data, inputs it into a fully connected layer-sized O, and applies softmax to derive class probabilities for each image, indicating the likelihood of each class.

Algorithm 1: Hybrid Vision Transformer

	input:	Image data: $X \in \mathrm{R}$^ $(N \times H \times W \times C)$, where N is the batch size, H is the height, W is the width, and C is the number of channels Patch size: P Embedding dimension: E No. of layers: L No. of attention heads: A Hidden layer dimension: H_dim Output dimension: O
	Output: Class probabilities for each input image	
1	Apply a CNN module to the input image to extract features	
2	Split the image into non-overlapping patches of size P × P	
3	Generate positional encodings for each patch and add them to the embedded patch vectors	
4	for i = 1 to L do:	
5		Compute self-attention scores for each patch
6		Apply softmax to obtain attention weights
7		Weighted sum of the values to compute attention output

(continued)

(continued)

Algorithm 1: Hybrid Vision Transformer

```
    Apply a linear transformation to the attention output
    Add residual connections and layer normalization
    Apply a linear transformation
    Apply activation function (e.g., ReLU)
    Apply another linear transformation
    Add residual connections and layer normalization
End
Aggregate patch representations (e.g., mean pooling)
Feed the aggregated representation to a fully connected layer with output dimension O
Apply softmax activation to obtain class probabilities
```

This methodology aims to provide more accurate and insightful Twitter data sentiment analysis by fusing the advanced contextual understanding of the RoBERTa including traditional approaches such as Naïve Bayes transformer model with the text preprocessing and tokenization strengths of NLTK.

4 Result and Discussion

An extensive examination of the data supplied on various hybrid vision transformer models for CCTV surveillance-based accident detection. We'll go over the formulas and relevance of the metrics (Table 1).

The proportion of correctly classified samples, including both true negatives and true positives, compared to the total number is known as accuracy [3] in binary classification using Eq. (8). The highest accuracy was attained by Efficientnet_Vit (94.55%), closely followed by Resnet-152_Vit (94.32%). The least accurate network was Mobilenet_Vit (83.86%) as shown in Fig. 5.

Formula:

Table 1 The table compares hybrid vision transformer models on different metrics. ViT paired with ResNet-152, VGG-19, EfficientNet-ViT, Mobilenet_Vit and densenet-201_Vit

Models	Accuracy	Loss	Precision	Recall	F1-score
Vit	49.97	0.84	49.94	99.9	66.64
Vgg-19_Vit	93.41	0.22	92.28	93.64	66.67
Resnet-152_Vit	94.32	0.24	98.44	91.82	66.67
Mobilenet_Vit	83.86	0.34	91.34	77.27	66.67
densenet-201_Vit	87.05	0.29	94.52	80.0	66.67
efficientnet_Vit	94.55	0.15	90.13	98.18	66.67

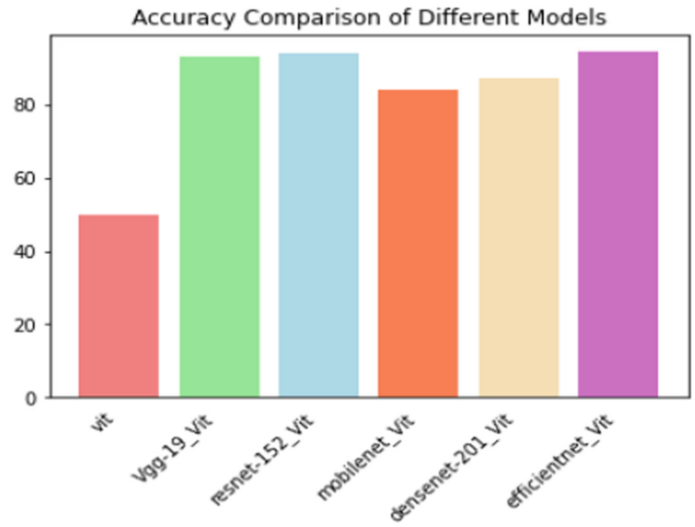

Fig. 5 Different models accuracy percentages

$$\text{Accuracy} = \frac{\text{TP} + \text{TN} + \text{FP} + \text{FN}}{\text{TP} + \text{TN}} \tag{8}$$

where:

True Positions (TP)	represents the count of samples accurately identified as positive.
True Negatives (TN)	indicates the quantity of samples correctly recognized as negative.
False Positives (FP))	denotes the instances wrongly classified as positives.
False Negatives (FN)	signifies the count of samples inaccurately labelled as negative.

Loss is difference between the expected and actual values. Cross-entropy loss, which penalizes inaccurate classifications more harshly, is frequently employed in binary classification calculated using Eq. (9). Additionally, as represented in Fig. 6 Efficientnet_Vit had the lowest loss (0.15), demonstrating improved error-minimization capabilities of the model.

Formula:

$$\text{CrossEntropyLoss} = -\frac{1}{\text{N}}\sum_{\text{i}=0}^{\text{N}}\left(\left(1 - \text{y}_\text{i}\right)\log\left(1 - \widehat{\text{y}}_\text{i}\right) + \text{y}_\text{i}\log\left(\widehat{\text{y}}_\text{i}\right)\right) \tag{9}$$

where:

N represents total number of samples.

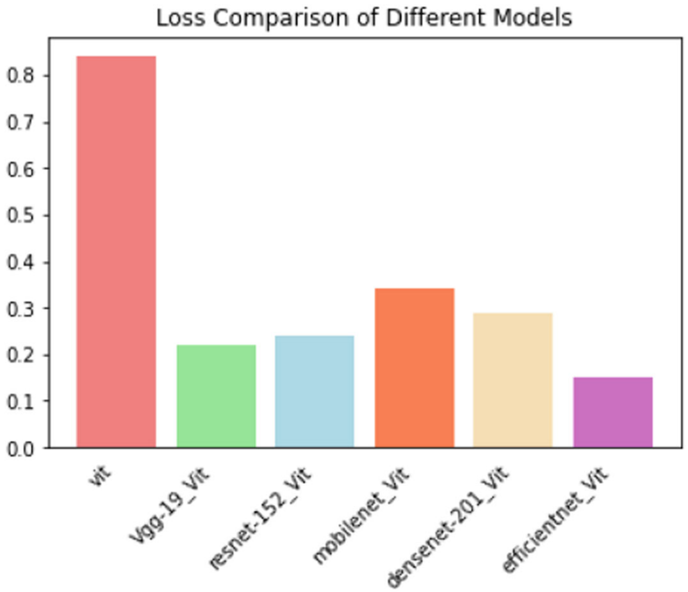

Fig. 6 Different models loss comparison percentages

y_i represents true label.
$\widehat{y}_i$ is the predicted probability of the sample being in the positive class.

The porportion of all positives forecast that ae true positive predictions is known as precision [3] using Eq. (10). It shows how well the model can prevent false positives. From Fig. 7 the highest precision (98.44%), Resnet-152_Vit, had fewer false positive predictions. The least precise network was Mobilenet_Vit, at 91.34%.

Formula:

$$\text{Precision} = \frac{\text{TP} + \text{FP}}{\text{TP}} \tag{10}$$

Recall [3] is the percentage of true positive predictions among all real positive samples, which is also referred to as sensitivity which is calculated using Eq. (11). It shows how well the model can capture good examples. With the highest recall (98.18%), Efficientnet_Vit was able to capture more positive instances. Recall was lowest for Mobilenet_Vit (77.27%) as represented in Fig. 8.

Formula:

$$\text{Recall} = \frac{\text{TP} + \text{FN}}{\text{TP}} \tag{11}$$

The harmonic mean of recall and precision is known as the F1-score [3]. It offers a compromise between recall and precision, and it’s frequently employed as a lone

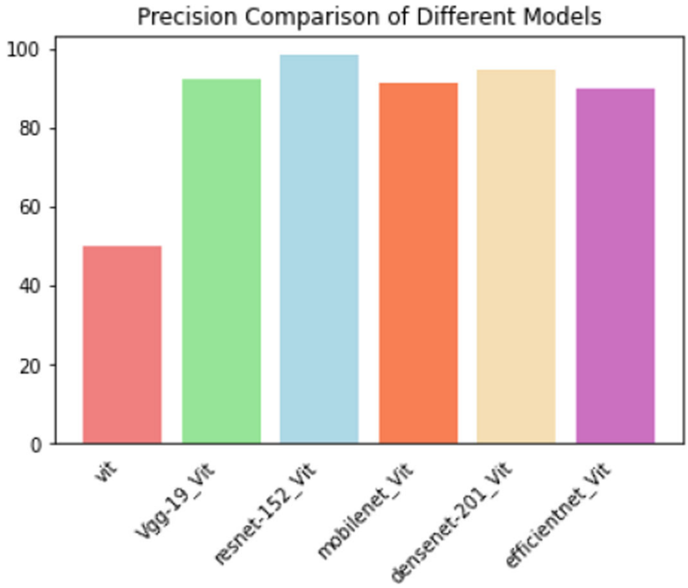

Fig. 7 Different models precision comparison percentages

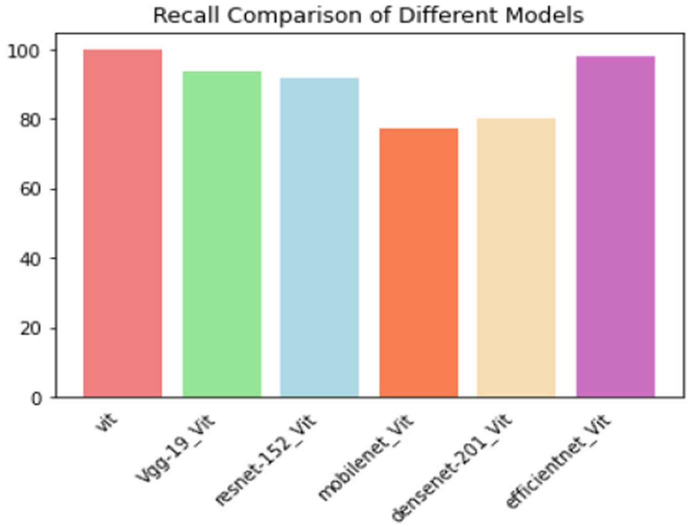

Fig. 8 Different models recall comparison percentages

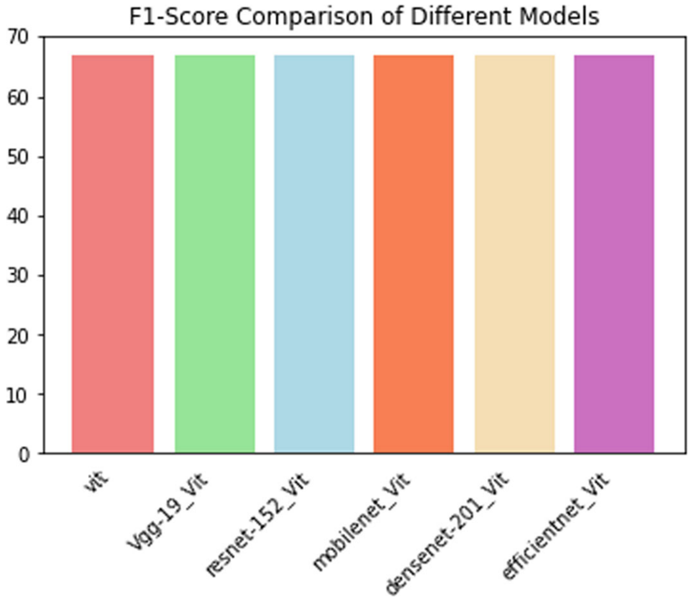

Fig. 9 Different models F1-score comparison percentages

metric for model evaluation using Eq. (12). Despite having varying precision and recall levels, from Fig. 9 we conclude that all models had the same F1-score (66.67%), suggesting a balance between the two parameters.

Formula:

$$F1 = 2 \times \frac{\text{Precision} + \text{Recall}}{\text{Precision} \times \ \text{Recall}} \tag{12}$$

The particular requirements of the application determine which model should be used. Over viewing Fig. 10 the Overall, Efficientnet_Vit works admirably, exhibiting balanced precision and recall, little loss, and good accuracy. However, Resnet-152_ Vit might be chosen if reducing false positives (with great precision) is essential. Similarly, Efficientnet_Vit would be the best option if maximizing true positives (high recall) is crucial.

5 Conclusion and Future Work

An excellent effort in road safety technology includes an automated system that uses Hybrid Vision Transformer models to detect accidents in the road. With the increase in video surveillance and modern traffic control systems, it is currently required to have creative solutions at the grassroots level to identify potential road dangers in minutes.

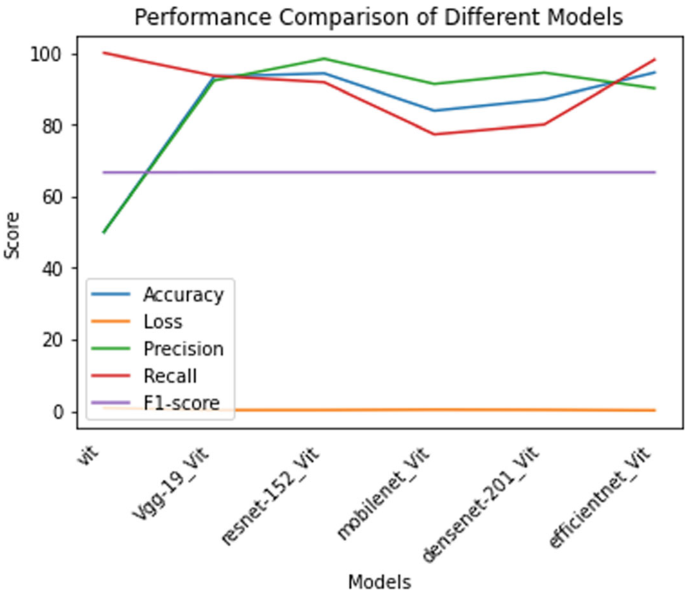

Fig. 10 Performance comparison of different models

The proposed method is thus a promising answer in this respect, via machine learning, which can process video data to analyze and decide different kinds of accidents instantly. Among its main advantages is the Hybrid Vision Transformer model, which is capable of processing and processing visual data from video streams effectively and speedily. This model has combined the best characteristics of transformers and CNNs, hence catching the spatial and temporal characteristics of the video input with great precision. The results indicate high accuracy and recall rates during both the training and validation phases, thus the model can identify traffic incidents with great efficacy. Apart from the instantaneous advantages of the proposed system for accident detection, the proposed solution can be implemented into the emergency response infrastructure. For example, using a GSM module for SMS alerts, the system can provide real-time notification of accidents to hospitals and emergency services to allocate resources better. Using computing modules like the Raspberry Pi, the system can even detect and process the accident instantly on the spot, within a shorter response time and a better overall system efficiency.

The future development will be geared towards implementing the system at the hardware level. This will mean the consolidation of all required elements of the computing and GSM modules in one platform capable of recognizing and notifying the concerned users in real-time over the incidences of road accidents. The system shall also be scalable and flexible, meaning it shall be deployable in a wide array of traffic scenarios and environments. Other factors being equal, the development of a system that would use Hybrid Vision Transformer models to recognize traffic accidents would be a significant step ahead in the technological science of road safety. This approach would go a long way in enhancing road safety by reducing the chances of violent deaths and subsequently enhancing skills in emergency reaction by machine learning and real-time data processing. The impact of the system on road safety would only escalate with future developments and system fine-tuning. Further outcomes are the saving of lives and reducing injuries on our roads.

References

1. World Health Organization (WHO): Road Traffic İnjuries—Fact Sheet. World Health Organization, Geneva (2024). Available at: https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries. Accessed Oct 2024
2. Basheer Ahmed, M.I.B., Zaghdoud, R., Ahmed, M.S., Sendi, R., Alsharif, S., Alabdulkarim, J., Krishnasamy, G.: A real-time computer vision-based approach to detection and classification of traffic incidents. Big Data Cognitive Comput. **7**(1), 22 (2023)
3. Joshi, R.M., Rao, D.S.: AlexDarkNet: hybrid CNN architecture for real-time traffic monitoring with unprecedented reliability. Neural Comput. Appl. **1**, 1–9 (2024)
4. Boon-itt, S., Skunkan, Y.: Public perception of the COVID-19 pandemic on Twitter: sentiment analysis and topic modeling study. JMIR Public Health Surveill. **6**(4), e21978 (2020). https://doi.org/10.2196/21978
5. Lee, I.J.: An accident detection system on highways through CCTV with Calogero-Moser system. In: 18th Asia-Pacific Conference on Communications (APCC), pp. 522–525. Springer, Heidelberg (2012)
6. Ckay16 (2024) Accident detection from CCTV footage. Kaggle (2024). Available at: https://www.kaggle.com/datasets/ckay16/accident-detection-from-cctv-footage. Accessed Oct 2024
7. Choi, J.G., Kong, C.W., Kim, G., Lim, S.: Car crash detection using ensemble deep learning and multimodal data from dashboard cameras. Expert Syst. Appl. **183**, 115400 (2021)
8. Khan, S.W., Hafeez, Q., Khalid, M.I., Alroobaea, R., Hussain, S., Iqbal, J., Ullah, S.S.: Anomaly detection in traffic surveillance videos using deep learning. Sensors **22**(17), 6563 (2022)
9. Hooda, R., Kawediya, R., Sonigara, K., Andhare, S.: Accident detection system using surveillance cameras. Int. Res. J. Eng. Technol. **7**(4), 2395–0056 (2020)
10. Zhang, Y., Sung, Y.: Traffic accident detection method using trajectory tracking and influence maps. Mathematics **11**(7), 1743 (2023)
11. Ghahremannezhad, H., Shi, H., Liu, C.: Real-time accident detection in traffic surveillance using deep learning. In: IEEE International Conference on Imaging Systems and Techniques (IST), pp. 1–6. Springer, Heidelberg (2022).
12. Ijjina, E.P., Chand, D., Gupta, S., Goutham, K.: Computer vision-based accident detection in traffic surveillance. In: 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), pp. 1–6. Springer, Heidelberg (2019)
13. Thakare, K.V., Dogra, D.P., Choi, H., Kim, H., Kim, I.J.: Object interaction-based localization and description of road accident events using deep learning. IEEE Trans. Intell. Transp. Syst. **23**(11), 20601–20613 (2022)
14. Pawar, K., Attar, V.: Deep learning-based detection and localization of road accidents from traffic surveillance videos. ICT Express **8**(3), 379–387 (2022)
15. Shaikh, A.I.: Smart accident detection and handling. In: Proceedings of an International Conference on Smart Systems and Technologies, pp. 1–8. Springer, Heidelberg (2023)
16. Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Houlsby, N.: An image is worth 16×16 words: transformers for image recognition at scale (2020). arXiv preprint arXiv:2010.11929
17. Tahir, M., Qiao, Y., Kanwal, N., Lee, B., Asghar, M. N.: Real-time event-driven road traffic monitoring system using CCTV video analytics. IEEE Access (2023)

18. Gupta, R., Kakkar, R., Tanwar, S., Garg, D.: Transfer learning and CNN-based vehicle identification approach for hit-and-run cases. In: Proceedings of the 3rd International Conference on Advancement in Electronics & Communication Engineering (AECE 2023), pp. 1–13. Springer, Heidelberg (2023)

Featuring Smart Parking Solutions in Smart Cities: VANETs Optimization Using AI and IoT

Bhupinder Singh, Anjali Raghav, and Christian Kaunert

Abstract Smart parking solutions are reshaping urban mobility easing congestion, reducing emissions, and improving transportation in smart cities. These developments cover the integration of various vehicular ad hoc networks (VANET) with artificial intelligence (AI) and Internet of Things (IoT). VANET facilitates real-time interaction between vehicles parking infrastructure and city management systems, enabling dynamic data-sharing for effective allocation of parking spaces. AI algorithms analyze data collected from sensors, cameras and V2V (vehicle to vehicle) communication, ranging from parking availability prediction, route optimization to minimizing a driver's time spent searching for a parking space. Likewise, those using IoT-based data sensors in parking slots provide space occupancy information to centralized platforms that guide drivers to free slots via mobile apps or in-vehicle navigation systems. That prevents excess fuel from being burned, and thereby helps lower traffic jams on roads caused by cars searching for parking. And with predictive analytics powered by AI we can predict peak hours and advise on how to better organize parking. Smart parking systems not only promote a more convenient parking experience, but they also play a vital role in strengthening environmental sustainability efforts by reducing vehicle emissions and fuel consumption. But the successful implementation of such systems base on the strong cybersecurity strategy to maintain data privacy and stability of communication in road networks of VANET. Building scalable and secure smart parking systems requires collaboration between urban planners, technology providers, and policy-makers. With the helping integration of VANETs, AI, and IoT with smart parking system of Infrastructure, it can provide us with the ability to leverage the real-time data in order to improve, optimize and augment smart parking system platform and create smarter and livable urban cities.

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Keywords Smart parking solutions · VANETs · AI in urban mobility · IoT · Traffic optimization

1 Introduction

Traditional parking systems based on manual ticketing and first-come-first-serve allocation belong in the past for modern fast-growing urban centers. Thus, smart cities are adopting emerging technologies to mitigate these challenges and develop sustainable, smart urban areas. There are serious dilemmas such as traffic jams and parking. Old methods of parking are time-consuming and increase the search for a parking lot [1]. The results are wasted fuel, polluted air, and raw nerves. AI, IoT, and VANETs are some of the technology solutions that have provided ample opportunity for real-time monitoring, predictive analytics, and automated management of parking spaces. Also, it integrates these technologies to provide the best parking experience in urban areas by eliminating conservative parking and traffic congestion. By integrating artificial intelligence with the Internet of Things (IoT) in smart parking systems, huge volumes of data can be gathered and examined in real-time. Internet of Things-powered sensors are embedded on parking lots, identifying whether the spaces are occupied. Data is sent to centralized management systems [2]. AI algorithms examine this data and forecast parking demand, streamline space allocation, and direct drivers towards vacant parking spots. AI-powered image recognition tech offers extra safety by identifying illegally parked cars and parking rule violations. Apart from focusing on positive environmental impact, these smart solutions also contribute to reducing emissions, increasing fuel economy, and maximizing the driving experience by decreasing the time that we waste in looking for parking. The ability of vehicles to communicate with infrastructure is a such example of how wireless communication through VANETs can optimize smart parking systems. VANETs, as a special case of mobile ad hoc networks, enable vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication that enables cars to share information about parking availability [2]. This connectivity enables drivers to find free, available spaces more quickly, contributing to reduced traffic congestion that is often witnessed when a vehicle circulates an area looking for parking. According to Ditta et al. [3], VANETs increase safety by sending warnings about route conditions, pedestrians, and unforeseen objects. The convergence of VANETs with artificial intelligence (AI) and the Internet of Things (IoT) fully changes parking management into a smart, automated, and highly efficient system that fits within the frame of smart cities.

Multiple technological components are considered in a smart parking system to ensure efficiency and sustainability. Sensors and RFID tags are installed to identify the presence of vehicles, and predictive analytics powered by artificial intelligence is used to approximate parking needs based on historical data and live elements. These long-term trends make Cloud Computing an important enabling technology that will be used to store and process large amounts of data that are generated by parking spaces to make timely decisions and orchestrate dynamic cooperation of many parking spaces. Users now have access to real-time data on parking availability through mobile applications and smart dashboards through ordinary parking solutions that allow them to reserve a parking spot and provide them with dynamic pricing updates to make parking much more efficient and consumer-friendly [4]. They make parking management simpler, smarter, and more attuned to the ebb and flow of urban life. A good part of managing parking spaces as well as traffic is also taken care of with the help of AI and IoT. AI deep learning models based on camera surveillance for Identifying empty parking spots in real-time image recognition. Then machine-learning algorithms analyze past trends, weather conditions and traffic patterns to predict which parking lots will be full and encourage drivers to take optimal routes. By using machine learning methods, dynamic pricing strategies can be established to adjust and smooth demand for parking across geographical areas and to avoid congested regions. Ultrasonic and infrared sensors embedded in smart buildings continuously update occupancy levels, while GPS and cloud-based systems aggregate and process the data to improve prediction accuracy [5]. Drone technology saves money, considerably; since there is no need for additional human intervention to unlock mechanisms, reducing costs associated with supervising devices or transport operations.

Adopting smart parking solutions with AI, IoT, and VANETs can help with several advantages, such as relieving congestion, improving fuel usage, and reducing environmental effects. These technologies reduce urban mobility and promote green and sustainable solutions by optimizing the time wasted searching for parking [6]. Additionally, intelligent parking systems align with the larger objectives of smart cities by improving resource efficiency, increasing safety, and elevating residents' quality of life. With more people moving into cities, the need for efficient intelligent parking solutions is only going to get stronger. While there are many advantages, the integration of AI and IoT-based smart parking systems presents a few challenges. Significant obstacles still exist: high upfront investment costs, data security and privacy concerns, and network reliability issues [7]. The DT and other ongoing advancements in 5G technology, edge computing, and blockchain security protocols will help to solve these security and convenience concerns related to smart parking solutions, enhancing their overall usage among users. Exploration and discovery in this field will play an essential role in the transformation of urban transport and the potential of smart cities. The integration of AI, IoT and VANETs in smart parking systems not only solves the problem of urban mobility and parking but also fosters the development of smart cities in general [8].

2 Smart Parking Solution Enhancing Efficiency and Sustainability

With the rapid growth of cities and their populations, street parking spots remain few and difficult to find. Traditional parking systems are heavily reliant on human efforts or outdated technologies, which leads to challenges such as traffic congestion, fuel wastage, and pollution. In this regard, several smart parking solutions have been introduced to overcome these challenges, involving advanced technologies such as Internet of Things (IoT), Artificial Intelligence (AI), and Vehicular Ad hoc Networks (VANET), etc. They provide real time information on parking resources, optimizing the use of spaces and enhance urban travel experience [9].

IoT-based sensors lie at the heart of smart parking systems, detecting the occupancy of parking spaces and communicating this data in real time to centralized management platforms. These sensors embedded in parking lots or on streets use ultrasonic, infrared, or even magnetic field detection and usage to know if a space is occupied. The information gathers and is processed to notify drivers through mobile apps, digital signboards, or navigation systems. Eliminating the trouble for the drivers to search for the parking themselves and reducing the congestion and the emission during the process [10]. Moreover, payment process for parking is now automated due to IoT sensors making the whole process faster, smoother, and cashless.

Predictive analysis powered by AI also contributes significantly to optimizing parking, which forecasts demand through historical patterns and real-time conditions. By processing huge quantities of information, such as traffic patterns, weather conditions, and peak usage hours, machine-learning algorithms predict parking occupancy rates. This allows for a form of dynamic pricing, where the parking fee can increase with demand to redistribute vehicles away from congested areas. The parking lots benefit from advanced security measures, as AI-based image recognition technology helps identify unauthorized vehicles, enforce parking standards, and prevent fraudulent behavior [11]. Moreover, AI-enabled chatbots and voice assistants enhance the user experience by guiding the user to the park in real-time and answering questions quickly.

The integration of Vehicle Ad hoc Network (VANET) with smart parking systems enables efficient vehicle-to-infrastructure communication and data exchange. Also, CARthage equipment enables Vehicle-to-vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication, facilitating communication between vehicles to exchange and share real-time information regarding the availability of parking spaces [12]. The personal parking information is connected, and it saves time for drivers looking for parking, which reduces the congestion of the road and enhances the traffic flow. Preventive NAT Physics is also, play a major role in road safety, They warn owners about extreme traffic conditions, pedestrian crossings, and etc. Artificial intelligence integrated with VANETs and the Internet of things (IoT) supports automated decisions like booking parking spaces beforehand according to predictive analytics and real-time availability.

Smart parking systems benefits in many ways like it lessens carbon emissions, it increases fuel saving and it also improves urban mobility. By reducing the duration vehicles are focused on looking for parking, these contribute to lower levels of air pollutants and help organizations to achieve city sustainability targets. Smart parking solutions also help municipalities cut operational costs by reducing the manual monitoring and enforcement. They are also create new revenue generation opportunities via dynamic pricing models and demand-model-based parking management [13].

While smart parking systems offer various advantages, there are challenges that need to be addressed for effective implementation. The main bottleneck is the high upfront investment for installation of IoT sensors, AI driven platforms and VANET communication networks. Before implementing systems of this nature, municipalities and private organizations have to see if the cost–benefit ratio makes sense. Moreover, the fact that IoT-based smart parking solutions involve the collection and transmission of sensitive user information raises issues of data security and privacy. Data encryption and adherence to data protection regulations are crucial for maintaining user trust and system security [14].

Network Reliability: Smart parking systems rely on continuous transmission of data between various devices, hence another critical challenge is network reliability. In low-network-coverage regions, real-time updates, which may be out of date, are inefficient. Smart parking solutions can use ultra-fast communication speeds and reduced latency thanks to the development of 5G technology and edge computing. Automated payment systems with blockchain technology can also enhance security by creating transparent and immutable records of transactions.

Researchers are actively studying different approaches in smart Parking system. The next step in smart parking evolution is the implementation of autonomous parking systems, where self-driving cars navigate the parking lot themselves and park without human intervention. Utilizing artificial intelligence-driven image detection, lidar technology, and sophisticated navigation algorithms, these systems detect open spaces and carry out careful parking operations [15]. Moreover, the incorporation of smart grids and renewable energy sources into parking infrastructures can also facilitate sustainability through charging stations for electric vehicles (EVs) in smart parking infrastructure.

With the increasing urban populations, the need for smart parking solutions will just increase. Urban planners and policy makers need to work together with technology developers and private stakeholders to create smart parking systems that support overall smart city initiatives. Through the application of AI, IoT, and VANETs, cities must improve traffic optimization, and minimize environmental emissions, while enhancing citizens' overall quality of life. Moving from traditional parking practices to intelligent, automated systems is an important part of building a more sustainable and technologically enhanced urban future.

3 Vehicular Ad Hoc Networks (VANETs) in Smart Parking

Vehicular Ad Hoc Networks (VANETs) play an essential role in Intelligent Transportation Systems (ITS) by allowing data exchange between vehicles and infrastructure. They enable efficient real-time data exchange between connected vehicles and parking systems, improving road safety, traffic management, and parking efficiency [16]. VANETs are also used in intelligent parking solutions to alleviate congestion with parking management, where vehicles demonstrate the ability to communicate among themselves and exchange parking information among them, thus enabling a reduction in congestion and improved urban mobility. Through vehicle-to-vehicle (V2V) as well as vehicle-to-infrastructure (V2I) communications, VANETs allow drivers to quickly locate open parking and reduce fuel consumption, improving overall smart city efficiency.

Urban drivers struggle with the biggest challenge of lack of real-time parking information which leads to needless traffic and air pollution. To overcome this problem, however, the idea of a Vehicle Ad hoc Networks (VANETs)' enables vehicles to communicate among themselves and with the roadside infrastructures to exchange information regarding free parking spots. Dynamic uncertain parking space sharing allows vehicles to take benefits through V2V and V2I communication to decrease the parking period, when searching for empty parking spots. This provides better movement of traffic and lower carbon emissions [17]. They also enable smart traffic systems by linking to AI-powered analysis algorithms that predict parking needs and adjust parking spaces in real time.

VANET Framework for Smart Parking Optimization

The fundamental components of a VANET-based smart parking system are as follows. A set of these components i.e. On-Board Units (OBUs), the Roadside Units (RSUs), and Cloud-Based Servers is used to effectively manage parking space utilization and guide drivers to the required parking spaces. On-Board Units (OBUs): OBUs are placed on-board (in-vehicle) systems that allow direct communication with parking infrastructure and other vehicles. These OBUs typically gather real time information on parking availability, traffic conditions, and other environmental data, which is then processed to the cloud. These units also allow communication between vehicles so that drivers share parking information and increase the efficiency of parking [18]. AI-based functionality, such as predictive based on historical and realtime data, can be embedded in OBUs integrated into more advanced VANET enabled smart parking systems.

OBUs also allow drivers to reserve parking it means we can actually pay in advance for a parking spot with a connected application. As a driver enters a congested area, the OBU can issue automated routing to the closest open parking lot, inferred by AI based predictions. Moreover, through communication with OBUs, collision avoidance systems can be utilized to prevent vehicle accidents while navigating parking facilities, thus increasing parking lot safety [19].

Roadside Units (RSUs) Roadside Units (RSUs) are fixed infrastructure that transmits parking information between vehicles and cloud servers. These units are usually installed at road intersections, parking lots and smart roadways to provide continuous communication between parked vehicles and vehicles searching for parking space. More specifically, RSUs act as data relay nodes, sending real-time parking status updates from Internet of Things (IoT)-based parking sensors to cars equipped with On-Board Units [20].

Reducing the Data Flow in Smart Parking using RSUs One core advantage that RSUs offer for smart parking is the capability to optimize data flow, thus decreasing the network congestion. Instead of bombarding cloud-based servers with constant queries for parking information, RSUs serve as local processing hubs, forwarding only the relevant, necessary information. With this practice, parking details will be communicated heavily with less buffering and timely choices for the drivers. Furthermore, RSUs can be coupled with smart traffic lights, which can change according to the parking demand and traffic flow to improve urban mobility [21].

Beyond just optimizing parking space usage, RSUs also increase the safety and security of parking structures. Computer vision technology and AI-powered surveillance systems can be installed in these units to keep an eye on parking/halt authorization and roadway transgressions. As the next step in law enforcement integration, RSUs architecture can even be integrated with law enforcement databases, making this solution one of the ultimate smart parking solutions at the junction of security, regulation, and parking technology.

Cloud Servers for Predictive Parking Analytics: The cloud servers in VANET-enabled smart parking systems are necessary for storing and processing potentially huge amounts of parking data. These servers collect real-time information from OBUs, RSUs, and IoT-based parking sensors for predictive parking analytics [22]. Machine learning algorithms process data trends related to parking demand, traffic patterns, and vehicle trajectories to predict parking availability and recommend routes for drivers.

Utilize Big Data Analytics for Dynamic Pricing: Cloud-based Parking Systems can apply Dynamic Pricing Models by using Big Data Analytics to dynamically increase parking fees based on demand, this encourages the effective use of existing parking spaces. For instance, charging higher fees for parking in high-traffic, congested areas and using peak pricing to discourage unnecessary use, and lower fees in areas with relatively higher vacancy rates. Intelligent pricing strategies like such can help optimize and monetize urban parking spaces for municipalities [23].

Mobile apps can be integrated into Cloud-based parking management to enable drivers to access real-time parking availability, get navigation assistance and make cashless payments. Highly specialized AI and machine learning application algorithms create this through recommendation engines that be horizontal to be user based; and work as an application inside the application; predicting which way a driver goes the most, analyzing the vehicle size and past parking behavior (whether or not it overpays due to a wrong input). Moreover, cloud-based systems enable integrating blockchain technology for secure, tamper-resistant automated parking fee collection.

4 Integration of AI and Machine Learning in Parking Optimization

Smart parking systems integrated with artificial intelligence (AI) and machine learning (ML) revolutionize urban mobility through efficiency, reduction of congestion and an overall better user experience. Old school parking systems depend on both manual tracking and basic sensor-based data gathering methods, resulting in a high degree of inaccuracies and lags. Artificial Intelligence (AI) and Machine Learning (ML) revolutionize this process, utilizing massive amounts of real-time data to ensure the most optimized allocation of parking spaces, predict demand, and apply dynamic pricing [24]. Through these intelligent algorithms, the seamless coordination between the IoT-based sensors, vehicular networks (VANETs), and cloud-based analytics becomes possible, along with providing timely, accurate parking information to the drivers all-time.

Parking Optimization with: A New Approach

These AI-powered parking optimization systems leverage big data analytics drawn from a variety including cameras, Internet of Things (IoT) sensors, GPS data, and historical parking records for real-time guidance and predictive analytics [25]. These systems can leverage computer vision, deep learning, reinforcement learning, and neural networks to process and interpret data in an efficient manner. AI-powered parking solutions help with the following: May result in better traffic flow and reduced congestion; Reduced fuel consumption and environmental benefits; Dynamic Pricing Improved Revenue Generation; Enhanced security and fraud detection in the parking management; Tailored advice on where to park for drivers; Smart Parking: Key AI-ML Techniques; Deep Learning Based Image Recognition for Camera Based Parking Monitoring.

Deep learning, which falls under the umbrella of machine learning, is employed in camera-based smart parking systems for vacant space identification, unauthorized vehicle detection, and violation monitoring. Convolutional Neural Networks (CNN) analyse the real-time camera footage taken from parking lots and street-side parking areas as an important part of this process. These CNN models are designed to Rahman et al. [26].

This enables the elimination of electronic tags or physical sensors, leading to a decrease in infrastructure costs and an increase in the efficiency of the parking management process through the use of deep learning and computer vision (CV) techniques [27]. With improving algorithmic detection, AI-driven surveillance cameras not only make infrastructure and businesses more secure but also analyze and catch any suspicious events in real-time.

Adaptive Parking Pricing and Availability Predictions with Reinforcement Learning

Reinforcement learning (RL) is a cutting-edge AI technique that allows intelligent parking systems to make real-time, data-driven decisions on parking prices and availability predictions. RL algorithms learn from historical data over time in a manner improving their tactics to maximize usability and income [28].

Dynamic Pricing: RL-based algorithms use demand-sensitive dynamic pricing. For example, rates ramp up at peak hours when there are too many cars looking for parking, and rates drop at off-peak hours to encourage use of underutilized parking spaces.

Demand Forecasting: Historical and real-time data on parking occupancy is analyzed through these models indicating the future demand which ensures the perfect space utilization.

Allocation of parking space: RL optimizes the allocation of parking spaces taking into consideration vehicle type, reservation, and driver preference.

They benefit the users by making the parking process more convenient for them, and generate higher revenue for city administrators while ensuring fair distribution of parking spaces through efficient algorithms [29].

Predicting Vacant Spaces with Sensor Data: Use of Neural Networks instead

Neural networks: IoT-based car parking sensors are able to identify the presence of the vehicle, duration of parking, and movement patterns [30]. These types of networks can receive sensor input and interpret it to:

Neural Networks (NNs) that identifies complex data patterns of parking demand and re-allocate space as needed through a multi-layered architecture. RNN, LSTM Models: RNN, LSTM Model is very helpful for time-series data of the dataset to predict the peak time and off-peak time parking availability during the day [31].

AI & ML Are Being Integrated in Smart Parking Systems

Smart cities capitalizing on the heavily advantageous potential of AI and ML for the optimization of parking integrate these technologies as a part of cloud-based parking management platforms [32]. These platforms ingest data from a wide variety of data sources, such as: IoT-enabled parking sensors; Deep-learning models with surveillance cameras; Vehicle-to-Infrastructure Communication Using (VANETs); Real-time parking guidance through mobile apps. AI-enabled parking systems also facilitate automated reservation systems, allowing drivers to reserve parking spaces ahead of time via mobile apps. These reservations are constantly recalibrated using AI-based predictive algorithms to avoid conflicts and maximize space efficiency [33].

5 Role of IoT Enabled Smart Parking Infrastructure

Leveraging various technologies such as RFID tags, ultrasonic sensors and GPS trackers, IoT-enabled smart parking infrastructure is helping cities manage parking spaces efficiently (24/7) by providing real-time information about presence and movement of vehicles. A combination of advanced sensors, cloud computing, and mobile applications are mapped out to ensure a seamless experience for both parking space owners and users as the system operates. It is an efficient smart parking system that consists of four key components: smart sensor, cloud, mobile applications, etc. Smart sensors are the building bricks of an IoT based smart parking system. Ultrasonic sensors or similar are used deployed in the parking slots to check if the parking slots are occupied or available [34]. When a vehicle parks or departs, the sensor senses the state of changing occupancies and updates the cloud system in real-time. This enables continuous parking space monitoring and ensures that users receive real-time information. Ultrasonic sensors, for example, measure distance from sensor to vehicle, thus accurately detecting if a space is open or occupied. Ultrasonic sensors are not the only devices you can use for tracking. These devices are capable of detecting a vehicle that is either entering or exiting from a parking facility and relaying this information back to the master system.

IoT based smart parking system cloud integration Within this cloud-based platform, the sensors send the data they collect to be processed and analyzed in real-time. Cloud computing also enabled the system to process data in bulk, and fuel parking information aggregation across multiple locations. By processing complex data in seconds, the users are presented with information on which parked cars have been freed up which can be accessed through mobile apps. In addition, need-based charging models and proper resource management of the parking space are also enabled by using Cloud integration. Mobile applications have also significantly improved the user experience significantly by offering easy access to parking availability along with the ability to make reservations [35]. These applications give users the ability to search for available parking spaces in real-time, see parking options by location and even reserve spaces in advance. The mobile apps are usually linked to the navigation, directing users straight to the available parking space. Moreover, these applications provide some exclusive features like payment gateways through which users can pay for parking digitally and they do not need to get any physical payment method. Such an amalgamation of comfort and productivity, IoT enabled mobile apps eradicate any parking system hassles.

6 System Architecture for AI and IoT Optimization VANET Parking

The proposed system architecture for AI and IoT-optimized VANET parking proves to be an advanced and highly efficient solution with respect to the conventional parking spaces. This system provides a framework that interweaves Artificial Intelligence (AI), Internet of Things (IoT), and VANETs to augment driving protocols while concurrently facilitating parking space authority to help monitor and allocate parking spaces more effectively [36]. It is made up of four different, yet interrelated layers: Perception Layer, Network Layer, Processing Layer, Application Layer. This solution includes several layers, and each layer serves an important purpose in allowing the smart parking system to operate efficiently, making it one of the most advanced solutions for cities.

Data Collection: The Perception Layer is the first level of the system that is responsible for collecting real-time data about the parking environment. This layer employs different IoT sensors like ultrasonic sensors, cameras, RFID tags, and GPS devices to identify vehicles and analyze parking space occupancy and traffic data. Sensors are placed in strategic points such as parking slots, roads, and vehicles to collect valuable information (for instance: if a space is free or occupied, where is available space, if the vehicles have broken on their way to parking, etc.). The perception layer also gathers environmental data (like weather or traffic density) that may impact demand for parking [37]. Real-time data gathered at this level becomes the foundation for the whole system function, used in all levels of further analysis and procedures. The Network Layer enables a seamless exchange of information between vehicles, IoT devices, and the parking infrastructure. The function of the Transport Layer is to guarantee the real-time transmission of data collected within the Perception Layer towards the central processing system. In this layer systems called VANETs, which are ad-hoc networks, are used to allow vehicles and infrastructure to communicate directly with each other (not through a central server). VANETs enable vehicles to communicate with each other and parking infrastructure, keeping the parking system responsive and flexible [38].

AI can analyze usage patterns to identify anomalies where unauthorized vehicles are parked in reserved space. This predictive ability allows for the dynamic management of parking spaces, resolving parking resources in an effective and efficient manne [39]. This is the sixth layer, it constitutes the front end of the system, providing interface to drivers to get access to smart parking system. Using phone applications or in-car navigation systems, users can find parking in real time, including addresses and, when necessary, price. Data about available and gauged spots are shared through the application layer, that is the part that allows users to book a parking spot upfront, pay for the parking fee, and receive navigation directions to the nearest available parking space. It also shows notifications regarding availability of parking to let the drivers know where they would be able to park. This layer focuses on user interfaces that make the overall user experience more enjoyable, less frustrating, and more convenient for parking in these crowded urban environments [40].

7 Advantages of AI and IoT Driven Smart Parking

Benefits of smart parking using AI and IoT

The convergence of Artificial Intelligence (AI) and Internet of Things (IoT) in Vehicle Ad Hoc Networks (VANET) enabled smart parking systems offer a myriad of advantages that can revolutionize urban mobility. The combination of these technologies offer numerous benefits for drivers, city planners, and the environment by optimizing parking procedures [41]. Benefits of AI and IoT-Powered Smart Parking Solutions: Professional Summary of Key Aspects.

Reduced Congestion

Immediate Impact: Smart Parking Alleviates Road Congestion One of the major applications in terms of IOT and AI is smart parking systems. In normal situations, motorists waste time driving around parking lots or roads searching for an empty space. This search is a substantial factor in traffic congestion, especially in large cities with high population density. AI and IoT-enabled systems help drivers locate available parking spaces quickly and easily, meaning they spend less time searching [42].

For instance, AI algorithms can study parking patterns and begin directing drivers to the closest available spot based on real-time data optimizing the use of available parking spaces. Some businesses even deploy IoT sensors in the parking spaces to check whether that space is occupied or free and send the information to a central system [43]. It sounds that system takes the data, processes it, and delivers it to drivers through mobile apps or in-car navigation systems. Less time spent searching for a spot means less congestion on the road, contributing to smooth transportation flow and improving system productivity.

Improved Fuel Efficiency: The time looking for a parking space is often the result of valuable fuel consumed. Drivers will circle city blocks repeatedly, burning fuel while searching for an open space. This inherent fuel consumption not only translates to greater operating costs for drivers but also contributes to greenhouse gas emissions, as drivers must burn more fuel. The future of US truck driver pay to upend the status quo [44].

This inefficiency is reduced with smart parking systems. With real-time data from the Internet of Things sensors, drivers can query whether parking spaces are available before reaching their destination. It takes the guesswork out of finding a parking space and directs drivers to an open one quickly, saving time and fuel. This streamlining of parking leads to fuel savings, which reduces transport costs for the person and increases the city fuel efficiency [45].

Reduced Emissions and Environmental Impact: Traditional parking methods at hotels are under scrutiny for their environmental impact. As traffic jams get worse and drivers seek parking, gas usage rises and so do carbon emissions and air pollution. Air pollution has been linked to many health problems, including respiratory diseases and cardiovascular problems, according to the World Health Organization.

Integrating AI and IoT within smart parking can also help to reduce emissions. The main goal of AI-based parking systems is to prevent the time that people spend looking for a parking lot to minimize the time the car stays in idle or stays in movement without a need. Less time spent idling means less pollutant output from vehicle exhausts. Furthermore, optimized parking systems may decrease the flow of some vehicles during parking search peak times, like rush hours and holidays, reducing overall traffic and emissions levels [46].

Smart parking systems also promote EV usage by incorporating EV chargers into the parking management process. This reduces vehicle dependency that is ka-pow on fossil fuel, which is a good contribution towards a cleaner, greener environment. More environmentally friendly cities are designed as when optimized parking systems help reduce carbon footprint. Enhanced User Experience: With the help of AI and IoT-based smart parking solutions, the user experience for drivers can be significantly improved. Drivers had to spend time in getting around huge parking lots or searching for a parking space along the streets within the city in earlier parking systems. Smart parking systems help create a more streamlined and efficient experience, to make parking as frictionless as possible [47].

With the help of IoT sensors and AI algorithms, real-time navigation leads drivers to available parking spaces without them ever having to stress over wandering around mining for a location. Parking availability is integrated with mobile applications, in-car navigation systems or embedded GPS devices that enable users to plan their parking ahead of time or on the go [48]. Certain smart parking systems come with reservation functionalities that allow users to reserve parking spaces in advance for their required duration, ensuring that they have a guaranteed spot waiting for them. Furthermore, AI-based intelligent parking systems can also customize the user's experience by learning individual preferences and providing personalized recommendations. For instance, the system can recommend parking spots close to a driver's destination, or keep it apprised of availability of spots, pricing on those spots, or distance to certain amenities. By tailoring the parking experience to the needs of the driver, it increases convenience and offers a better overall experience.

8 Challenges in Implementing Smart Parking Solutions

Although the AI and IoT-enabled smart parking system has various advantages, their implementation comes with some challenges. These challenges include financial, privacy, technical, and scalability issues that need to be overcome to ensure efficient deployment and widespread adoption [49].

The main hurdles for smart parking implementation include traversal cost to deploy smart parking infrastructure. To build a complete system, IoT sensors, cameras, cloud computing services, and high-speed communication networks need to deploy; These elements need to be carefully installed in the parking lots and the urban sites to allow for immediate detection of free spaces and to send the data to the database and get real-time updates. Cost is further increased with software development for user interfaces (UI), mobile applications, and AI-driven predictive analytics [50]. Municipalities and private parking operators in developing parts of the world face a particularly relevant financial challenge because budget constraints preclude the adoption of smart parking technologies. Additionally, long-term maintenance, regular software upgrades, and the need for new hardware add to costs over time, making cost a major hindrance in widespread implementation.

Data privacy and cybersecurity risks are another big concern. AI and Internet of Things (IoT)-based smart parking solutions are based on the real-time tracking of vehicles and users, and this makes it even more likely that external parties may access data without authorization and engage in illegal surveillance. Cybercriminals can take advantage of system vulnerabilities to gain access to sensitive user data, including vehicle tracking information and payment credentials. The other side of using so many cameras and sensors is that it can create ethical dilemmas around user privacy, as driving in public and private parking lots can feel like being watched everywhere. Another issue is that data may be used by unauthorized third parties such as advertisers or governmental departments. However, to address these issues, Implementing strong encryption standards, data anonymization techniques, and strict access controls are essential. Governments and regulatory authorities must also impose regulations on privacy in order to protect user data and prevent such misuse [51].

Ensuring the network's reliability remains one of the key challenges in the successful implementation of smart parking solutions. These systems are dependent on constant and real-time communication between sensors, cloud servers, and mobile applications. Disconnections cause incorrect parking availability data to appear, delayed notifications, and system failures. In cities with too many cars, continuous connection is challenging due to network interference and congestion. Moreover, smart parking systems in conjunction with VANETs demand stable links for their efficient performance. Given that these networks can the blaring of directions can potentially lead to the navigating drivers receiving incorrect guidance, it could significantly decrease the overall efficiency of the system during the downtime or the communication failure. While 5G and DSRC protocols can improve network reliability and the road safety that follows, however, deploying them at scale is a rich-man's game [52]. Lastly, the scalability limitations remain a major challenge, especially in fast growing urban collision. With population growth and increasing vehicle ownership around the world, smart parking systems will need to adapt to the growing demand for parking spaces. Nevertheless, the development of further infrastructure to support this is limited in many scenarios by space and cost constraints to create more sensing, storage and communication nodes. In addition, due to a lack of standardization, interoperability problems occur when implementing different smart parking systems in different places. The solution to scalability challenges often lies in AI-powered optimization algorithms and modular system architectures, but applying these techniques successfully requires careful consideration and investment [53].

9 Future Research Directions

Because AI and IoT in VANETs have developed swiftly to modernize smart parking. Nonetheless, to ensure its long-term sustainability and efficacy, further research needs to be carried out to address key areas such as security, computational efficiency, seamless connectivity, and automation. Smart Parking Systems Enhanced with Emerging Technologies4 Integrating emerging technologies such as blockchain, edge computing, and 5G can further enhance smart parking systems to cope with the increasing demands of urban mobility.

This will be one of the areas with great potential for studying since blockchain can be used for secure parking transactions. The use of more efficient smart parking systems brings forth concerns such as data privacy, security, and financial transactions. This is because traditional centralized databases are susceptible to cyber threats, hacking, and data breaches. This is where blockchain technology comes into play; its decentralized and tamper-proof nature can make parking transactions transparent and secure. Blockchain smart contracts can perform payments with both reducing fraud and eliminating middlemen [54]. Moreover, throughout this information can be stored on blockchain securely, enabling just a selective end-users gain access to the sensitive details. Subsequent studies are needed to design effective consensus mechanisms that minimize transaction costs, as well as design optimized blockchain frameworks that facilitate the integration of blockchain in VANET-based parking systems.

Edge computing, another important area of research, can help us with real-time parking updates and, hence, reduce latency. In a traditional approach, cloud-based smart parking systems process data in a centralized manner, with information from vehicles and parking sensors being transmitted to cloud servers leading to delays in data reception and transmission. It helps in the processing of data closer to the source where it is generated, making way for instantaneous decision-making and real-time responses [55]. As an example, IoT sensors can collect parking occupancy data, which can be analyzed quickly in free data at the edge of the network rather than depending on cloud infrastructure. Further studies are needed to find optimal placement and cluster considerations for edge nodes, energy-efficient processing of data, and AI-driven decision-making for maximizing the responsiveness of smart parking systems. Moreover, the combination of federated learning and edge computing can facilitate the creation of collaborative AI models, promoting privacy-preserving data analytics in various locations [56].

Integration of 5G technology in VANET-based smart parking is another area that deserves significant research effort. Existing smart parking solutions generally use 4G LTE and Wi-Fi networks which can fail to deliver the speed and reliability required for real-time communication. With 5G, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, particularly in a dynamic environment through V2V can be greatly improved, benefiting the connected and intelligent transportation development. 5G allows ultra-low latency and high bandwidth, supporting real-time parking recommendations, remote vehicle monitoring, and AI-driven automation. Yet, elements like infrastructure rollout, energy consumption, and network interference remain issues to be solved. More studies on smart parking, optimizing 5G network architectures, developing efficient use of the spectrum, and securing text messages in areas of high congestion should be done in the future [57].

The more important research direction is autonomous parking systems, as they use AI-based automation to allow vehicles to park themselves. In recent years, advancements in computer vision capabilities, rapid expansion of deep learning technologies, and sensor fusion approaches have accelerated the development of autonomous parking systems that can find open spots, navigate complex parking structures, and park vehicles without human input. Large parking behavior data enables machine learning algorithms to learn from this and make better decisions leading autonomous vehicles to efficient parking even in crowded spaces [58]. Moreover, when integrated with IoT sensors, the system can provide real-time updates for parking availability, directing driverless vehicles to the nearest open parking space. Research is needed in improving AI models for autonomous parking, including sensor accuracy and fail-safe algorithms to mitigate collisions and parking failures. Moreover, the regulatory landscape must adapt to the evolving technological capabilities of autonomous vehicles, with policies addressing liability issues, insurance matters, and other relevant concerns [59].

The other essential element that needs research work is energy efficiency of AI and IoT enabled smart parking solutions. With more IoT devices and more AI-based computations, we have a lot more queries to be made, and this impacts on energy consumption and environmental sustainability. Additional studies are needed to investigate energy-aware computational algorithms, low energy smart space IoT sensory devices, and renewable energy systems to energize smart parking facilities. As an example, using solar-powered IoT sensors and AI-based energy management systems to decrease the carbon footprint of smart parking applications. AI-based demand-response mechanisms can maximize parking space utilization and mitigate excess energy consumption [60]. It is necessary to conduct research on the development of smart parking systems concerning the improvement of the user experience and accessibility. Presently, smart parking solutions are all about urban drivers, it should be more versatile, catering to differently abled and elderly drivers in the future as well. Voice-activated parking assistance via AI and personalized navigation systems, as well as parking spaces designed for wheelchair users can lead to a better experience for users. Additionally, augmented reality (AR) and virtual reality (VR) research can offer novel interactions that present parking status in AR or a VR environment, providing either intuitive or immersive parking directions [61].

Interoperability and standardization are also key areas in smart parking solutions. By deploying different smart parking technologies in each city or by parking operator, incompatibility or fragmentation occurs. Moreover, to seamlessly integrate smart parking systems throughout multiple regions, the development of standardized protocols is imperative in future studies. By adopting AI-powered interoperability frameworks, data can be shared between various parking management systems, ensuring an efficient and scalable approach. Furthermore, studies on cloud computing data sharing patterns may facilitate real-time information transfer, providing drivers with access to parking availability information from various areas. Lastly, the social and economic effects of AI and IoT-based smart parking need to be studied [62]. Smart parking solution offers time efficient convenience, but it is also crucial to establish an impact assessment of urban planning, employment and transport policies. Future research should then analyze the potential displacement of traditional parking attendants to the cost of smart parking systems for low-income communities and the broader implications for public transportation. Research on smart parking incentives, dynamic pricing schemes, and public–private partnerships can also inform sustainable and equitable smart parking policy [63].

10 Conclusion

The intelligent transport systems are designed to hold human-centered traffic management that transforms the way we park vehicles with the introduction of AI and IoT-enabled VANETs that gives a system smart parking by making best use of allocated space, less congestion, and improve transport in cities. Smart parking solutions address parking issues in modern cities by utilizing real-time data, predictive analytics, and vehicle communication. Additionally, the recent amalgamation of advanced technologies like AI-powered automation, blockchain-based security, edge computing, and 5G connectivity has made these systems even more efficient and robust. However, there are still some challenges to be overcome, including high implementation costs, data privacy issues, network reliability, and scalability issues. Nonetheless, with continued research and avenues for technology improvements, the challenges associated with smart parking will be addressed to help create smarter and secure smart-parking systems. Our findings lay the groundwork for further research in domains such as Blockchain for secure parking transactions, Edge Computing for real-time processing of data, 5G for improved connectivity, and AI-based autonomous parking systems. Moreover, finding energy-efficient solutions, developing standardization frameworks, and creating inclusive user experiences will help shape smart parking technologies. With cars becoming increasingly ubiquitous as urbanization expands, parking needs to be more of a focus so smart parking will be more important. Alongside, to realize smart parking systems, collaborative efforts among governments, researchers, and industry leaders must take place in order to develop smart parking systems that are sustainable, scalable, and user-friendly. The future of smart parking is promising and has the potential to revolutionize urban mobility in a seamless, integrated, and greener way through the application of AI, IoT, and other emerging technologies.

References

1. Sahu, B.L., Chandrakar, P.: Blockchain-oriented secure communication and smart parking model for internet of electric vehicles in smart cities. Peer Peer Networking Appl. **18**(1), 1–17 (2025)
2. Priyadarshi, S., Subudhi, S., Kumar, S., Bhardwaj, D., Mohapatra, H.: Analysis on enhancing urban mobility with IoT-integrated parking solutions. In: Interdisciplinary Approaches to Transportation and Urban Planning, pp. 143–172. IGI Global (2025)
3. Ditta, A., Ahmed, M.M., Mazhar, T., Shahzad, T., Alahmed, Y., Hamam, H.: Number plate recognition smart parking management system using IoT. Meas. Sens. **37**, 101409 (2025)
4. Asmare, M.G., Kumar, V., Singh, S.K., Ravikumar, R.N., Khan, N.: Secure and intelligent smart parking: a Blockchain, federated learning, and digital twin approach. In: Sustainable Smart Cities and the Future of Urban Development, pp. 395–416. IGI Global Scientific Publishing (2025)
5. Hooda, S., Sarika, S., Sharma, V.K.: Optimizing urban intelligence: a comprehensive study on IoT with edge computing in smart cities. Integr. AI Quantum Comput. Semicond. Technol. 441–456 (2025)

6. Shaker, H., Sharef, Z.T., Abbas, S., Khan, S.: Vehicle to infrastructure routing protocols: AI and finance perspectives. In: Innovations in Blockchain-Powered Intelligence and Cognitive Internet of Things (CIoT), pp. 341–388. IGI Global Scientific Publishing (2025)
7. Sood, S.K.: A multifaceted analysis of intelligent vehicle route optimization. IEEE Trans. Intell. Transp. Syst. (2025)
8. Behura, A., Kumar, A., Jain, P.K.: A comparative performance analysis of vehicular routing protocols in intelligent transportation systems. Telecommun. Syst. **88**(1), 26 (2025)
9. Singh, A.K., Kumar, D.A.: Data optimization in the IoT for improving traffic management (2025). Available at SSRN 5101310
10. Jethwa, R., Pradhan, R.R., Mishra, S., Balamurugan, S.: The evolution of Cobots in intelligent transportation systems. In: Intelligent Robots and Cobots: Industry 5.0 Applications, pp. 65–84
11. Nwobodo, L.K.: Intelligent traffic control, gathering and monitoring traffic data using CCTV images. Contemp. Res. Anal. J. **2**(01), 40–51 (2025)
12. Zemmouchi-Ghomari, L.: Artificial intelligence in intelligent transportation systems. J. Intell. Manuf. Spec. Equipment (2025)
13. Telikani, A., Sarkar, A., Du, B., Santoso, F., Shen, J., Yan, J., et al.: Unmanned aerial vehicle-aided intelligent transportation systems: vision, challenges, and opportunities. IEEE Commun. Surv. Tutorials (2025)
14. Babu, C.S., Anniyappa, C.A., Raut, A.: Toward seamless mobility: Integrating connected and autonomous vehicles in smart cities through digital twins. In: Digital Twins for Smart Cities and Villages, pp. 169–187. Elsevier
15. Mezni, H., Yahyaoui, H., Elmannai, H., Alkanhel, R.I.: Personalized service recommendation in smart mobility networks. Clust. Comput. **28**(3), 164 (2025)
16. Arumugam, G., Packianathan, R., Malaiarasan, A., Natarajan, S.K.: The role of sensors in shaping future transportation systems. In: Driving Green Transportation System Through Artificial Intelligence and Automation: Approaches, Technologies and Applications, pp. 485–509. Springer Nature Switzerland, Cham (2025)
17. Wazid, M., Singh, J., Pandey, C., Sherratt, R.S., Das, A.K., Giri, D., Park, Y.: Explainable deep learning-enabled malware attack detection for IoT-enabled intelligent transportation systems. IEEE Trans. Intell. Transport. Syst. (2025)
18. Choudhury, R.A., Singh, M., Kumar, R., Devi, R., Sharma, S., Singh, J., et al.: A critical review on the role of artificial intelligence in transforming the transportation sector. Arch. Computat. Methods Eng. 1–18 (2025)
19. Tsybina, E., Lebakula, V., Zhang, F., Hu, Q., Laskey, K.B.: Smart cities: the data to decisions process. Nat. Cities 1–9 (2025)
20. Pradhan, D., Tun, H.M., Naing, Z.M., Oo, T., Wah, N.K.S.: Secure M2M communication for 5G-enabled cities with its challenges. In: 5G Green Communication Networks for Smart Cities, pp. 261–282. Apple Academic Press (2025)
21. Al-Heety, O.S., Zakaria, Z., Abu-Khadrah, A., Ismail, M., Shakir, M.M., Alani, S., Alsariera, H.: Traffic congestion control with emergency awareness and optimized communication infrastructure using reinforcement learning and non-dominated sorting genetic algorithm. IEEE Access (2025)
22. Sethuraman, R., Venkataramani, K., Yamuna Devi, M.M., Subbaraj, S.: Enhancing autonomous vehicle performance with ensemble weighted support vector-based optimization in cloud. Clust. Comput. **28**(3), 192 (2025)
23. Visvizi, A., Malik, R., Guazzo, G.M., Çekani, V.: The Industry 5.0 (I50) paradigm, blockchain-based applications and the smart city. Eur. J. Innov. Manage. **28**(1), 5–26 (2025)
24. Sharma, S.K., Hans, R.: From code to sustainability: the impact of computer science in advancing sustainable development. In: Role of Science and Technology for Sustainable Future: Volume 2-Applied Sciences and Technologies, pp. 547–582. Springer Nature Singapore, Singapore (2025)
25. Tiwari, P.K., Prakash, S., Tripathi, A., Yang, T., Rathore, R.S., Aggarwal, M., Shukla, N.K.: A Secure and robust machine learning model for intrusion detection in internet of vehicles. IEEE Access

26. Rahman, A., Islam, J., Kundu, D., Karim, R., Rahman, Z., Band, S.S., et al.: Impacts of blockchain in software-defined Internet of Things ecosystem with Network Function Virtualization for smart applications: present perspectives and future directions. Int. J. Commun. Syst. **38**(1), e5429 (2025)
27. Manasrah, A., Yaseen, Q., Al-Aqrabi, H., Liu, L.: Identity-based authentication in VANETs: a review. IEEE Trans. Intell. Transp. Syst. (2025)
28. Shankar Baggam, D., Rani, S.: Autonomous systems for 5G networks: a comprehensive analysis of features toward generalization and adaptability. Curr. Future Cell. Syst.: Technol. Appl. Challenges 107–137 (2025)
29. Mohsin, A.S., Choudhury, S.H., Muyeed, M.A.: Automatic priority analysis of emergency response systems using internet of things (IoT) and machine learning (ML). Transp. Eng. 100304 (2025)
30. Singh, S.K., Kumar, S., Garg, S., Arora, S., Sharma, S.K., Arya, V., Chui, K.T.: Blockchain-based data security in smart cities: ensuring data integrity and trustworthiness. In: Digital Forensics and Cyber Crime Investigation, pp. 17–41. CRC Press (2025)
31. Johnson, R., Kim, A., Chen, E., Taylor, J., Brown, M., Lee, S.: Utilizing Geospatial Analysis in Smart City Data Visualization
32. Rattan, A., Pal, A.R., Gurusamy, M.: Quantum computing for advanced driver assistance systems and autonomous vehicles: a review. IEEE Access (2025)
33. Kumari, A., Kumar, S., Raw, R.S., Bohra, N.: Clustering in vehicular Ad Hoc network: a bibliometric analysis. SN Comput. Sci. **6**(2), 112 (2025)
34. Sahu, V.K., Pandey, D., Singh, R., Pandey, V.: A rigorous examination and optimization of access control mechanisms across the strata of IoT networks
35. Behura, A., Patra, R.: Challenges and future prospects of integrating quantum computing into intelligent transportation systems: exploring quantum innovations in transportation. Integr. AI Quantum Comput. Semicond. Technol. 183–208 (2025)
36. Zahid, H., Zulfiqar, A., Adnan, M., Iqbal, M.S., Shah, A.: Transforming nano grids to smart grid 3.0: AI, digital twins, blockchain, and the Metaverse revolutionizing the energy ecosystem (2025)
37. Zhang, H., Li, D., Xue, T.: Introduction to vehicular social networks. In: Intelligent Resources Management for Vehicular Social Networks: Societal Perspectives and Current Issues in the Digital Era, pp. 1–34. Springer Nature Switzerland, Cham (2025)
38. Etaiwi, W., Idwan, S.: Traffic management systems: a survey of current solutions and emerging technologies. J. Comput. Soc. Sci. **8**(1), 7 (2025)
39. Ruchika, S.: Exploring machine learning applications for enhancing security and privacy in multimedia IoT: a comprehensive review. Mach. Learn. Multimedia 34–49 (2025)
40. Okere, E.E., Balyan, V.: Sixth generation enabling technologies and machine learning intersection: a performance optimization perspective. Future Internet **17**(2), 50 (2025)
41. Kim, S.K., Vong, H.C.: Secured network architectures based on blockchain technologies: a systematic review. ACM Comput. Surv. (2025)
42. Ahmed, M., Soofi, A.A., Raza, S., Khan, F., Ahmad, S., Ullah, W., Han, Z.: Advancements in RIS-assisted UAV for empowering multi-access edge computing: a survey. IEEE Internet Things J (2025)
43. Dilshad, M., Syed, M.H., Rehman, S.: Efficient distributed denial of service attack detection in internet of vehicles using Gini index feature selection and federated learning. Future Internet **17**(1), 9 (2025)
44. Liu, Z.: Optimized cooperative data transmission in two-tier NB-IoT networks. Computing **107**(1), 1–31 (2025)
45. Ngoupayou Limbepe, Z., Gai, K., Yu, J.: Blockchain-based privacy-enhancing federated learning in smart healthcare: a survey. Blockchains **3**(1), 1 (2025)
46. Muktar, B., Fono, V., Nouboukpo, A.: Towards green transportation: predictive modeling of intersection congestion using machine learning for sustainable urban traffic management (2025)
47. Ma, C., Huang, X., Wang, K., Zhao, Y.: Prediction of remaining parking spaces based on EMD-LSTM-BiLSTM neural network. J. Traffic Transp. Eng. (English Edition) (2025)

48. Zhang, T., Kong, F., Deng, D., Tang, X., Wu, X., Xu, C., Deng, R.H.: Moving target defense meets artificial intelligence-driven network: a comprehensive survey. IEEE Internet Things J. (2025)
49. Alatabani, L.E., Saeed, R.A.: XAI applications in autonomous vehicles. In: Explainable Artificial Intelligence for Autonomous Vehicles, pp. 73–99. CRC Press (2025)
50. Mallala, B., Tajuddin, M.F.N., Thanikanti, S.B., Manyam, R.R.: Experimental analysis using IoT based smart power quality analyser system with remote data access and GSM alerting mechanism. IEEE Access (2025)
51. Chen, C., Liu, Z., Yu, Y., Jin, F., Han, W., Berretti, S., et al.: A deep learning-based traffic classification method for 5G aerial computing networks. IEEE Internet Things J. (2025)
52. Kumar, G., Saha, R., Conti, M., Rodrigues, J.J.: TAURITE: stackelberg equilibrium in blockchained energynet through electric vehicles. IEEE Trans. Intell. Transp. Syst. (2025)
53. Zheng, C., Peng, X., Wang, Z., Ma, T., Lu, J., Chen, L., et al.: A review on blockchain applications in operational technology for food and agriculture critical infrastructure. Foods **14**(2), 251 (2025)
54. Dong, Y., Peng, Q., Houichi, M., Alshahrani, R., Abeba, S., Park, K.: Efficient algorithm for resource optimization in optical communication networks. Opt. Express **33**(2), 2138–2157 (2025)
55. Sahare, M., Maheshwary, P., Dwivedi, V.K.: A fuzzy approach for congestion avoidance in FANET and IoT. Nine **34**(35), 36 (2025)
56. Bao, S., Sun, Z., Cruickshank, H.: Securing massive IoT using network slicing and blockchain. In: Security and Privacy for 6G Massive IoT, pp. 129–153 (2025)
57. Tripp-Barba, C., Aguilar-Calderón, J.A., Urquiza-Aguiar, L., Zaldívar-Colado, A., Ramírez-Noriega, A.: A systematic mapping study on state estimation techniques for lithium-ion batteries in electric vehicles. World Electr. Veh. J. **16**(2), 57 (2025)
58. Zhao, W., Lv, C., Yang, L., Xu, S., Du, Z.: Transformer-based sparse data collection and reconstruction in UAV-enabled Iot. Available at SSRN 5111347
59. Kumaran, K.S., Khekare, G., Thanu Athitya, M., Arulmozhivarman, A.: Integrating blockchain, internet of things, and cloud for secure healthcare. Indonesian J. Electr. Eng. Comput. Sci. **37**(2), 928–936 (2025)
60. Satpathy, S.P., Mohanty, S., Pradhan, M.: A sustainable mutual authentication protocol for IoT-Fog-Cloud environment. Peer-Peer Networking Appl. **18**(1), 1–23 (2025)
61. Xiao, X., Li, C., Wang, X., Zeng, A.: Personalized tourism recommendation model based on temporal multilayer sequential neural network. Sci. Rep. **15**(1), 382 (2025)
62. Hiendro, A., Wigyarianto, F., Husin, F.: Real-time paddy grain drying and monitoring system using long range-internet of things. Int. J. Electr. Comput. Eng. (2088–8708) **15**(1) (2025)
63. Cheng, Z., Zhu, J., Feng, Z., Yang, M., Zhang, W., Chen, J.: Driving safety risk analysis and assessment in a mixed driving environment of connected and non-connected vehicles: a systematic survey. IEEE Trans. Intell. Transport. Syst. (2025)

Optimizing Smart Parking in Urban Spaces: AI-Driven VANET Models Using IOT Frameworks

Hrishikesh Kokate, Babasaheb Jadhav, and Shashi Kant Gupta

Abstract The rapid urban expansion and increasing vehicle count in modern cities have intensified the demand for efficient and flexible parking management strategies. This study explores the integration of AI and IOT technologies to improve VANETs for smart parking solutions in urban environments. It investigates how AI algorithms, combined with IOT-linked sensors and communication systems, can enhance parking operations, boost vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communications, and alleviate traffic congestion. The proposed framework employs machine learning techniques for predictive analytics and real-time data management to dynamically allocate parking spaces based on availability and demand patterns. It also evaluates how deep reinforcement learning influences the improvement of VANET routing protocols to increase data transmission efficiency and reduce latency. Additionally, this study highlights the significance of edge computing and cloud-based systems in enabling seamless data sharing and effective decision-making. The study emphasizes real-world applications and case studies that demonstrate the efficacy of AI-based VANET models by addressing significant issues such as data security, network scalability, and system interoperability. It also examines the potential of integrating blockchain technology to ensure data integrity and protect transactions in smart parking systems. The findings presented in this study aim to provide urban planners, policymakers, and technology developers with actionable insights for creating sustainable and smart parking solutions, thus promoting the overarching objective of smart cities and progress in urban mobility.

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1 Introduction

Urbanization is swiftly changing cities globally, resulting in higher population density, more economic activities, and greater vehicle ownership [10]. As cities grow, the need for effective transportation and parking systems increases considerably. Nonetheless, traditional parking systems find it difficult to handle this increase, leading to traffic jams, fuel loss, and ecological damage. Poor parking management not only impacts urban transportation but also leads to longer travel times and heightened frustration for commuters [7, 8].

1.1 Challenges in Traditional Parking Systems

Conventional parking systems mainly depend on manual oversight and fixed assignment strategies, resulting in ineffectiveness in busy urban areas [45]. Several of the main difficulties consist of:

(a) **Insufficient Real-Time Data**: Drivers frequently waste a lot of time looking for open parking spaces, resulting in unwarranted traffic jams.
(b) **Inefficient Use of Space**: The rigid and non-flexible assignment of parking spots leads to low usage during off-peak periods [36].
(c) **Traffic Jam and Pollution**: Cars looking for parking led to higher fuel usage and emissions.
(d) **Absence of Flexible Pricing Strategies**: Conventional parking systems do not incorporate dynamic pricing models that can enhance space usage according to demand.

1.2 The Need for Smart Parking Solutions

To tackle these inefficiencies, intelligent parking solutions have arisen as a revolutionary method for urban mobility. These systems combine cutting-edge technologies like AI, IOT and VANETs to deliver real-time information on parking availability, enhance parking space distribution, and alleviate congestion [12]. Intelligent parking not only improves driver ease but also aids sustainability initiatives by lowering carbon emissions and minimizing fuel waste.

1.3 Role of AI, IOT, and VANETs in Modern Parking Management

(a) **Artificial Intelligence (AI)**: AI-based algorithms examine past and current data to forecast parking needs and efficiently direct drivers to free spaces. Machine learning algorithms improve decision-making in shifting environments.
(b) **Internet of Things (IOT)**: Sensors and devices equipped with IOT capabilities track parking availability and send real-time information to cloud platforms, facilitating smooth interaction between vehicles and infrastructure.
(c) **Vehicular Ad Hoc Networks (VANETs)**: VANET systems support vehicle-to-vehicle and vehicle-to-infrastructure interactions, allowing for smart routing and flexible parking options.

Utilizing AI, IOT, VANETs and intelligent parking systems establish a dynamic, real-time environment that improves urban parking, alleviates congestion, and boosts overall urban mobility. This study examines how these technologies can be combined to create a strong, AI-based parking management system [21, 22] (Fig. 1).

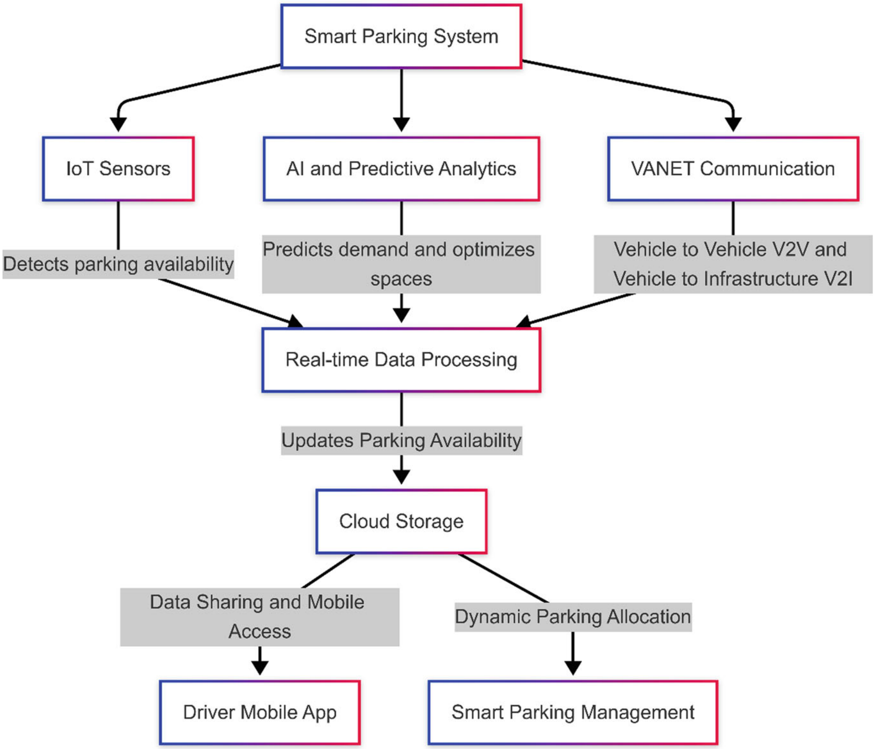
Smart Parking System
IoT Sensors
AI and Predictive Analytics
VANET Communication
Detects parking availability
Predicts demand and optimizes spaces
Vehicle to Vehicle V2V and Vehicle to Infrastructure V2I
Real-time Data Processing
Updates Parking Availability
Cloud Storage
Data Sharing and Mobile Access
Dynamic Parking Allocation
Driver Mobile App
Smart Parking Management

Fig. 1 Smart parking system architecture: integration of IoT, AI, and VANET

The diagram of the Smart Parking System Architecture demonstrates the integration of IoT sensors, AI algorithms, and VANET communication to establish an effective parking system. IoT sensors identify current parking availability, and AI analyzes this information to forecast demand and enhance space distribution. VANET facilitates uninterrupted communication between vehicles and infrastructure, allowing for real-time updates on parking availability via cloud storage. This information is subsequently communicated to drivers through mobile applications and digital displays, facilitating a seamless and smart parking experience.

2 Understanding Smart Parking Systems

2.1 Definition and Components of a Smart Parking System

A smart parking solution is a sophisticated technology that enhances the use of parking areas via real time tracking, automated choices, and efficient interaction between vehicles and infrastructure [16]. These systems utilize sensors, wireless communication networks, and data analysis to boost efficiency, lessen congestion, and enhance user experience.

A standard smart parking system includes these main elements:

(a) IOT-Equipped Sensors Placed in parking areas or along roadways, these sensors identify vehicle presence and deliver real-time occupancy information.
(b) Predictive Analytics Using AI ML algorithms examine past and present parking information to predict demand and improve space distribution [33].
(c) Cloud Based Data Processing: Centralized data storage and management systems enable instant decision-making and data sharing.
(d) Mobile and Web Applications: Intuitive applications allow drivers to verify parking spots, book reservations, and get navigation support.
(e) Dynamic Signage and Navigation Systems: Electronic displays and automated alerts direct drivers to available spaces, minimizing search duration.
(f) Automated Payment and Access Control: Intelligent parking solutions combine cashless transactions with automatic vehicle identification for smooth ingress and egress [23].

2.2 How IOT and AI Improve Parking Efficiency

The combination of IOT and AI greatly improves parking management efficiency by delivering real-time, data-informed insights.

(a) **Live Monitoring and Notifications**: IOT sensors observe parking availability and send real-time data, guaranteeing that users and managers receive current information.

(b) **Forecasting Demand with Predictive Analytics**: AI algorithms examine parking behaviors to foresee busy times and suggest ideal space distribution strategies [43].
(c) **Minimized Search Duration and Traffic Bottlenecks**: By directing drivers to the closest available parking spot, AI and IOT lessen avoidable vehicle movement and fuel usage.
(d) **Dynamic Pricing Systems**: AI-powered dynamic pricing modifies parking rates according to demand, fostering improved space usage and maximizing revenue.
(e) **Automated Violation Detection**: AI-driven monitoring systems can recognize illegal parking and send immediate notifications to officials.

2.3 The Role of VANETs in Communication Between Vehicles and Infrastructure

VANETs are essential for facilitating smooth communication between vehicles and intelligent parking systems [18]. VANET technology enables vehicles to exchange information among themselves & with roadside units or parking management systems.

Important roles of VANETs in intelligent parking solutions consist of:

(a) **Smart Navigation and Route Enhancement**: VANETs deliver live information on parking spaces and recommend optimal routes to reduce travel duration.
(b) **Dynamic Parking Allocation**: Cars can interact with parking systems to request and secure spaces in real-time.
(c) **Improved Safety and Security**: VANETs enable the sharing of notifications regarding parking dangers, theft threats, or emergencies.
(d) **Minimized Delay in Data Transfer**: By employing low-latency communication protocols, VANETs guarantee rapid response times for parking space notifications.

Smart parking systems transform urban mobility by combining IOT, AI, and VANETs, resulting in improved efficiency, sustainability, and user convenience in parking [11]. These technologies improve ease for drivers while also helping to lower environmental impact by decreasing unnecessary vehicle travel.

3 AI in Smart Parking

AI significantly transforms parking systems by improving decision-making, lowering congestion, and increasing the overall effectiveness of urban transportation. By utilizing AI-powered algorithms, intelligent parking systems can efficiently assign parking spots, forecast demand, and deliver real-time occupancy information, resulting in a smooth experience for both drivers and urban planners [21, 22].

3.1 AI-Powered Parking Space Distribution

Conventional parking allocation methods usually adhere to a fixed, first-come-first-served approach, resulting in poor space usage and longer search durations [49]. AI-powered parking space assignment systems address these constraints by:

(a) **Examining Real Time Traffic and Parking Information**: AI constantly evaluates live data from IOT sensors, cameras, and mobile apps to identify the most effective allocation of parking spaces.
(b) **Dynamic Space Reservation**: AI-powered systems enable drivers to book parking spaces ahead of time by utilizing predictive demand and past data.
(c) **Enhanced Space Optimization**: AI maximizes efficiency by redistributing available areas according to vehicle dimensions, length of stay, and changes in demand.
(d) **Automated Ingress and Egress Management**: AI-driven license plate recognition (LPR) systems enhance parking entry by automatically identifying and authenticating vehicles [24].

3.2 Machine Learning for Predictive Parking Insights

ML which is a component of AI, allows intelligent parking systems to evaluate large volumes of historical and real-time data to predict parking demand accurately. Several important applications consist of:

(a) **Forecasting Busy Periods and Demand Trends**: Machine learning models evaluate data points like time, weekday, and special occasions to project parking needs across various areas.
(b) **Suggesting Alternative Parking Solutions**: When main parking areas are occupied, ML-driven systems propose nearby alternatives considering historical user choices and current availability [37].
(c) **Dynamic Pricing Optimization**: Machine learning aids in the application of surge pricing models, causing parking charges to vary with demand, promoting a more efficient distribution of parked cars throughout available spots.
(d) **Traffic Flow Management**: Simulations powered by ML forecast and alleviate bottlenecks by modifying parking options in congested areas.

3.3 AI-Driven Real-Time Parking Space Occupancy Detection

AI improves parking occupancy monitoring by combining multiple data sources and increasing precision beyond conventional sensor-driven systems. A few essential AI-based strategies consist of:

(a) **Computer Vision and Image Recognition**: Surveillance cameras driven by AI utilize image recognition algorithms to accurately identify available and taken parking spaces [17].
(b) **Sensor Fusion Technology**: Integrating information from ultrasonic, infrared, and LiDAR sensors, AI improves precision in recognizing current parking occupancy.
(c) **Parking Violation Anomaly Detection**: Utilizing AI for anomaly identification aids in spotting unauthorized parking, vehicles that have overstayed, and illegal parking behaviors, activating automated notices for enforcement.
(d) **Collaboration with Smart City Infrastructure**: AI-driven parking occupancy solutions communicate with intelligent traffic signals and navigation platforms to deliver immediate information on parking availability.

Utilizing AI for assigning parking spaces, forecasting data analysis, and instantaneous occupancy monitoring makes smart parking systems increasingly efficient, adaptable, and focused on users. AI not only boosts convenience for drivers but also enhances city mobility by reducing congestion and optimizing space usage.

4 IOT Structure in Parking Solutions

The IOT is essential in converting traditional parking systems into intelligent, automated solutions. Parking systems enabled by IOT utilize interconnected sensors, wireless communication technologies, and cloud-based platforms to maximize space usage, decrease congestion, and enhance user experience [41]. Integrating IOT with intelligent devices, automobiles, and infrastructure allows for more efficient and responsive real-time monitoring and decision-making.

4.1 Function of IOT Sensors in Observing Parking Availability

IOT sensors form the core of intelligent parking solutions, delivering instantaneous information on space availability and vehicle activity. The sensors consist of:

(a) **Ultrasonic Sensors**: Placed in parking areas to identify vehicle occupancy through the reflection of sound waves.
(b) **Infrared (IR) Sensors**: Recognize vacant or filled areas by sensing thermal patterns or motion of objects.
(c) **Magnetic Sensors**: Installed within the pavement to detect vehicle closeness and motion by monitoring magnetic field variations.
(d) **CCTV and AI-Driven Image Recognition**: Cameras featuring AI-driven image processing identify free spaces without the need for extra physical sensors [6].

(e) **LiDAR and RFID Sensors**: Utilized for precise observation in automated parking areas and multi-story structures.

These IOT sensors send data to a central system, allowing for real-time observation, decreasing the time needed for parking searches, and improving urban traffic movement.

4.2 Protocols for Communication (V2I, V2V) to Enhance Parking Coordination

Smart parking systems based on IOT depend on effective communication between vehicles and their infrastructure. This is enabled through VANETs, which utilize two main communication protocols:

1. **Communication between Vehicles and Infrastructure (V2I)**:
    (a) Vehicles interact with intelligent parking systems through roadside units (RSUs) to obtain real-time updates on parking availability [15].
    (b) IOT-enabled parking facilities offer automated management of entry and exit utilizing license plate recognition or RFID technology.
    (c) Parking fee payments are simplified via mobile transactions or automated toll collection methods.
2. **Communication Between Vehicles (V2V)**:
    (a) Vehicles share data on nearby parking options, minimizing unnecessary searching.
    (b) V2V communication assists drivers in locating different parking alternatives by transmitting up-to-date information on crowding levels in multiple parking areas [5].
    (c) Autonomous vehicles utilize V2V communication to effectively organize self-parking actions.

Through the integration of V2I and V2V communication, IOT-driven parking systems improve parking coordination, reduce search durations, and enhance overall traffic control.

4.3 Combining IOT and Mobile Apps for Effortless Parking Solutions

Mobile applications powered by IOT are essential in offering users immediate parking help. Important features include:

(a) **Real-time Parking Availability Updates**: Users can monitor open parking spaces through a mobile app, minimizing unnecessary car travel [13].
(b) **Automated Parking Reservation**: Drivers can reserve parking spaces ahead of time and get navigational assistance.
(c) **Navigation Support and Route Enhancement**: GPS-equipped mobile applications direct drivers to the closest available spot with the least number of detours.
(d) **Digital Transactions and Cashless Payments**: IOT connects with mobile wallets, enabling smooth, contactless payments for parking [26].
(e) **Intelligent Notifications and Alerts**: Users are notified about open slots, time restrictions, and lapsed bookings.
(f) **Connection with Smart City Systems**: IOT-based parking applications interact with public transportation and city traffic networks for an enhanced travel experience.

Integrating IOT sensors, VANET communication protocols, and mobile apps, smart parking systems provide a smooth, data-informed, and user-centric solution for urban transportation [3]. These improvements aid in minimizing congestion, enhancing space usage, and boosting overall traffic efficiency.

5 VANET Models and Optimization

VANETs are essential in contemporary smart parking systems by enabling real-time communication between vehicles and their surrounding infrastructure. These networks establish a decentralized framework that allows vehicles to exchange information about parking availability, traffic situations, and navigation support, ultimately enhancing urban mobility [42]. The incorporation of AI, especially deep reinforcement learning, boosts VANET efficiency by refining routing protocols and data transfer.

5.1 Fundamentals of VANETs and Their Use in Parking Solutions

VANETs are specific type of Mobile Ad Hoc Networks (MANETs) intended for V2V and V2I interactions. They are made up of these essential components:

(a) **On-Board Units (OBUs)**: Set up in vehicles to enable wireless communication.
(b) **Roadside Units (RSUs)**: Stationary infrastructure that links vehicles to cloud-based parking solutions.
(c) **Wireless Communication Protocols**: VANETs utilize Dedicated Short-Range Communication (DSRC), Cellular-V2X (C-V2X), or 5G networks for instantaneous data sharing [30].

5.2 *Usage in Intelligent Parking*

(a) **Dynamic Parking Space Distribution**: VANETs allow vehicles to share real-time availability information with nearby motorists.
(b) **Adaptive Parking Reservations**: Cars can reserve parking spots in advance by utilizing real-time information from roadside units.
(c) **Traffic Flow Enhancement**: VANETs help redirect vehicles to vacant parking spots, minimizing traffic congestion.

5.3 *Enhancing VANETs Using Deep Reinforcement Learning*

(a) Deep reinforcement learning (DRL) has become a potent method for enhancing VANET-based parking solutions. Through ongoing learning from previous experiences and dynamically adapting decisions, DRL improves system efficiency.
(b) Forecasting Parking Demand Assessment: DRL algorithms examine past parking trends to anticipate peak demand times and assign spaces in advance [34].
(c) Adaptive Route Planning: Vehicles are directed to open spaces according to ongoing evaluations of demand and supply.
(d) Reduced Latency in Data Transfer: DRL enhances data transmission between vehicles and infrastructure, guaranteeing quicker response times.
(e) Communication with Energy Efficiency: DRL reduces unnecessary data transfers, saving energy in connected vehicles.

5.4 *Routing Protocols and Efficiency of Data Transmission in Smart Parking*

Effective routing is crucial for intelligent parking systems based on VANET to reduce communication delays and enhance vehicle flow. Important routing protocols consist of:

1. **Routing Based on Topology**:
    (a) Utilizes established network frameworks for communication.
    (b) Optimized Link State Routing (OLSR) guarantees reliable data communication between vehicles and RSUs [47].
2. **Routing Based on Position**:
    (a) Vehicles exchange GPS location information to enable immediate communication.

    (b) Greedy Perimeter Stateless Routing (GPSR) chooses the quickest route for data transfer.

3. **Routing Based on Clusters**:
    (a) Vehicles create compact communication groups to enhance network effectiveness.
    (b) Cluster-Based Directional Routing (CBDR) organizes vehicles by their location to enhance the speed of message transmission [1].
4. **Routing Enhanced by AI**:
    (a) ML algorithms forecast traffic jams and adapt data transmission in real-time.
    (b) Reinforcement Learning-Driven Routing (RLR) reduces transmission delays.

Through the combination of enhanced VANET models, deep reinforcement learning, and sophisticated routing protocols, smart parking systems attain quicker response times, less congestion, and a better experience for drivers. The collaboration between AI and VANETs will keep fueling advancements in smart urban parking systems [28] (Fig. 2).

The VANET-Based Parking Communication Model emphasizes the interaction between vehicles and roadside units (RSUs) for obtaining parking support. The RSUs connect to a cloud-based parking management system that utilizes AI to forecast space availability and assign spots instantly. After a spot is designated, navigation help directs the driver to the best location. Once parked, the system refreshes availability to assist other drivers, alleviating unnecessary congestion and enhancing traffic movement.

6 Technological Enablers

The swift progress in computing and networking technologies has greatly enhanced the effectiveness and dependability of smart parking systems [31]. State-of-the-art advancements like edge computing, cloud architectures, 5G technology, and blockchain are vital for improving parking management by enabling real-time data processing, fluid connectivity, and secure transactions.

6.1 Edge Computing and Cloud-Based Solutions in Parking Management

Intelligent parking solutions produce large quantities of data from IOT sensors, cameras, and vehicles equipped with VANET technology. Effective data processing

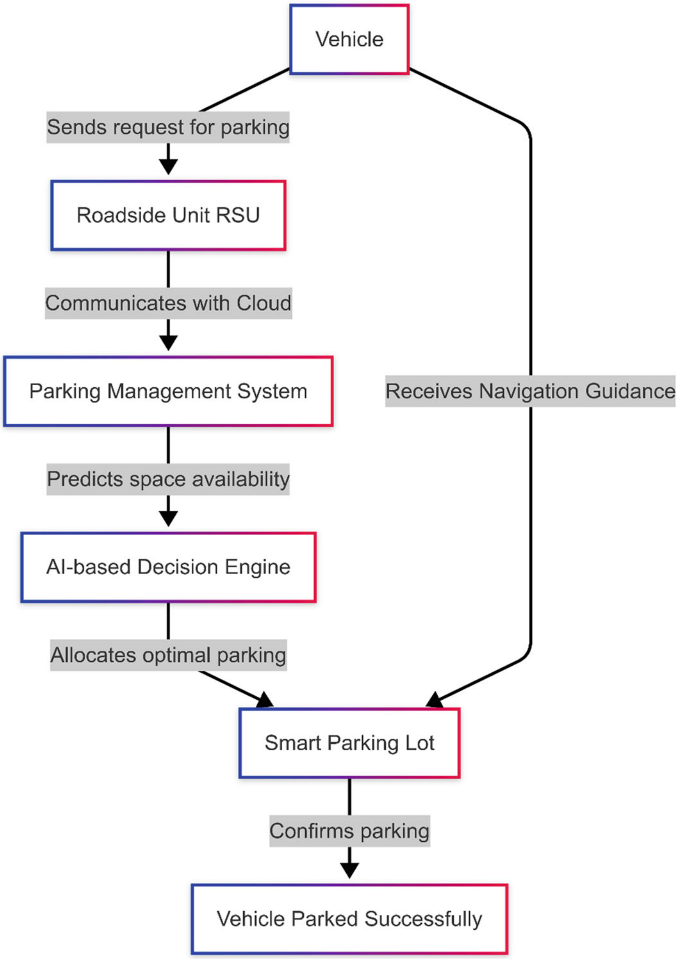
Vehicle
Sends request for parking
Roadside Unit RSU
Communicates with Cloud
Parking Management System
Receives Navigation Guidance
Predicts space availability
AI-based Decision Engine
Allocates optimal parking
Smart Parking Lot
Confirms parking
Vehicle Parked Successfully

Fig. 2 VANET-based parking communication model for real-time space allocation

is crucial for real-time decision-making, accomplished via edge computing and cloud architectures.

6.2 Edge Computing in Parking Solutions

(a) **Instant Data Processing**: Edge computing allows for local processing at parking sensors or roadside units, minimizing latency and reliance on centralized servers.

(b) **Quicker Decision-Making**: Parking availability, occupancy information, and automated space bookings are handled instantly at the edge, guaranteeing rapid responses for drivers.
(c) **Decreased Network Load**: By processing data nearer to the source, unnecessary transmissions to the cloud are reduced, enhancing bandwidth efficiency [48].
(d) **Improved Security**: Important vehicle and parking information stays within local networks, minimizing the chance of cyber threats [44].

6.3 Cloud-Driven Parking Administration

(a) **Centralized Data Storage**: Cloud systems gather and examine extensive datasets, enhancing predictive analytics for parking needs.
(b) **Scalability**: Cloud-based parking systems can effortlessly grow to support numerous city locations.
(c) **Remote Access and Control**: Parking administrators can oversee and control various lots from a single cloud interface.
(d) **Coordination with Smart City Ecosystems**: Cloud platforms link parking information with various smart city services, enhancing overall urban mobility [32].

6.4 The Impact of 5G and Low-Latency Networks on Enhancing VANET-Driven Parking:

The introduction of 5G networks transforms VANET-enabled parking systems by offering:

(a) **Extremely Low Latency Communication**: 5G guarantees almost immediate data transfer among vehicles, parking sensors, and management systems.
(b) **Increased Bandwidth for Instant Video Processing**: AI-driven cameras and LiDAR devices utilize 5G to send high-definition data for precise occupancy recognition.
(c) **Smooth Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) Communication**: 5G enhances the effectiveness of real-time parking assignment and route planning [9].
(d) **Assistance for Independent Parking**: Self-driving cars depend on 5G-enabled VANETs to steer, identify, and park on their own.

With 5G-enabled connectivity, intelligent parking solutions can function more effectively, lessen traffic, and improve the driver experience by delivering immediate updates on space availability.

6.5 *Blockchain for Safe Transactions and Data Accuracy in Smart Parking*

Blockchain technology tackles issues of security, transparency, and data integrity in smart parking systems by:

(a) **Guaranteeing Secure Parking Information**: Blockchain logs every transaction associated with parking bookings, payments, and occupancy changes in an unalterable ledger.
(b) **Safe and Clear Payment Handling**: Smart contracts on the blockchain facilitate automated, trust-free transactions through digital wallets or cryptocurrencies.
(c) **Averting Fraud and Unapproved Access**: Decentralized identity verification systems boost security by limiting unapproved access to parking areas [27].
(d) **Improving Data Exchange in Smart Cities**: Blockchain facilitates secure collaboration among parking operators, city officials, and transit services.

Integrating blockchain with IOT and AI enables smart parking systems to attain greater transparency, automated transactions, and improved user trust.

7 Challenges and Solutions in Smart Parking Systems

Although smart parking systems provide considerable benefits for urban mobility, their deployment presents numerous challenges. Challenges like data security, network scalability, interoperability, and budget limitations need to be tackled to guarantee the smooth functioning of smart parking systems. This part examines these difficulties and offers possible solutions.

7.1 *Issues Related to Data Security and Privacy*

Challenge: Intelligent parking solutions depend on IOT sensors, AI-based analytics, and cloud infrastructures, which produce and retain large quantities of sensitive information [47] such as:

(a) Information on vehicle registration.
(b) Information regarding user payments.
(c) Tracking location in real time.

These data points are susceptible to cyber-attacks, data leaks, and unauthorized access, creating risks for both users and service providers.

Solutions: To alleviate security risks, intelligent parking systems need to incorporate:

(a) **End-to-End Encryption**: Guaranteeing that all interactions among vehicles, sensors, and cloud servers stay protected [38].
(b) **Blockchain Technology**: Employing distributed ledgers to uphold clear and secure transaction records against tampering.
(c) **AI-Driven Anomaly Detection**: Utilizing machine learning techniques to identify and mitigate fraudulent activities or cyber risks.
(d) **Rigorous Access Regulations**: Using multi-factor authentication (MFA) and role-specific access for system users.

7.2 Challenges in Network Scalability

Challenges: With the growth of cities, the quantity of connected vehicles and IOT devices in intelligent parking systems rises dramatically. Conventional network designs might face challenges [39] with:

(a) **Heightened Data Traffic**: Resulting in delayed response times and reduced efficiency.
(b) **Elevated Latency in Real-Time Communication**: Impacting VANETs and automated parking assignment.
(c) **Restricted Bandwidth Distribution**: Leading to congestion in areas of high urban demand.

Solutions: To guarantee smooth scalability, intelligent parking solutions can implement:

(a) **5G and Edge Computing**: Minimizing latency and improving data processing speed through the facilitation of local data analysis.
(b) **Cloud-Native Microservices Architecture**: Enabling the modular enhancement of parking services while maintaining system performance [19].
(c) **Load Balancing Techniques**: Actively managing network traffic to avoid congestion and guarantee real-time functions.

7.3 Issues of Interoperability Among Various Smart City Infrastructures

Challenge: Intelligent parking solutions need to connect with different urban transport frameworks, such as:

(a) Networks of public transportation.
(b) Systems for managing traffic.
(c) Payment processors.

Nevertheless, varying standards, exclusive technologies, and insufficient uniform communication protocols may obstruct smooth integration.

Solutions: To improve interoperability, cities need to:

(a) **Implement Standardized Communication Protocols**: Utilizing universal frameworks such as Vehicle-to-Everything (V2X) and MQTT (Message Queuing Telemetry Transport) for IOT connectivity [35].
(b) **Activate Open APIs for Data Exchange**: Permitting external applications and services to connect with parking management systems.
(c) **Establish Smart City Data Centers**: Building integrated platforms that allow various urban services, such as parking, to securely share data [40].

7.4 Financial and Execution Challenges

Challenge: Implementing smart parking systems necessitates a considerable upfront investment in:

(a) Infrastructure (IOT devices, surveillance cameras, roadside units, cloud storage, etc.).
(b) Network Enhancements (5G, edge computing, and secure communication protocols).
(c) Software Creation (artificial intelligence algorithms, forecast analysis, and user interfaces).

Such expenses might deter small towns and private companies from utilizing smart parking systems.

Solutions: To alleviate financial obstacles, interested parties can:

(a) **Utilize Public–Private Partnerships (PPPs)**: Promoting collaborative investments between governments and technology suppliers [7, 8].
(b) **Adopt Pay-As-You-Go Models**: Enabling cities to progressively expand their smart parking systems according to demand.
(c) **Leverage AI-Based Cost Efficiency**: Anticipating demand and enhancing energy use to reduce operational expenses [25].
(d) **Pursue Government Grants and Subsidies**: Investigating funding options aimed at smart city projects [29] (Fig. 3).

The AI-Powered Intelligent Parking Process emphasizes the importance of AI in enhancing parking management. IoT sensors gather real-time information, which is analyzed by cloud-based AI algorithms to forecast demand, handle space distribution, and optimize driver routes. The AI system continuously refreshes parking availability and offers drivers navigation support through mobile apps and digital displays. Through constant observation and modification of parking space allocation, AI improves efficiency, lessens traffic, and lowers the duration drivers spend looking for parking areas.

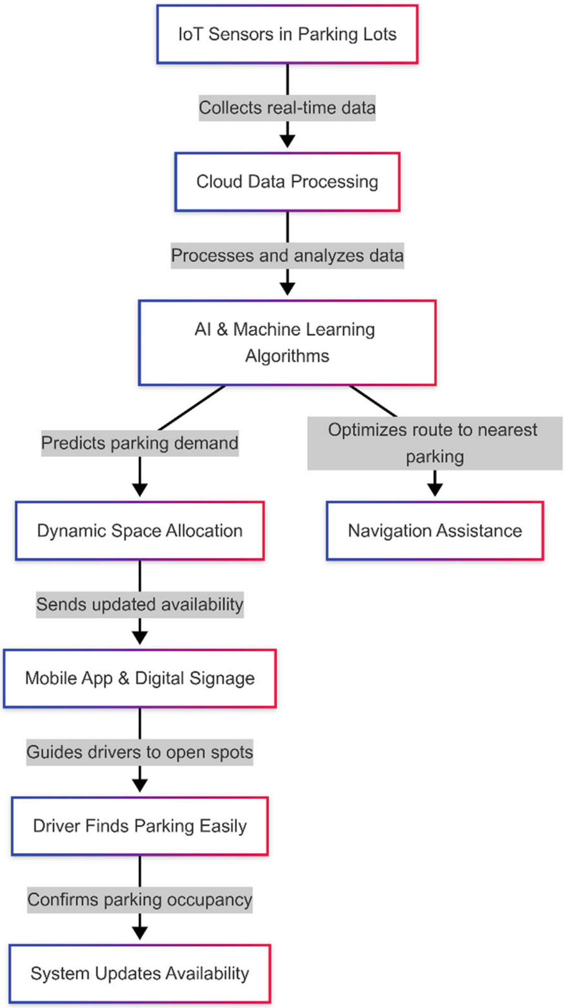
IoT Sensors in Parking Lots
Collects real-time data
Cloud Data Processing
Processes and analyzes data
AI & Machine Learning Algorithms
Predicts parking demand
Optimizes route to nearest parking
Dynamic Space Allocation
Navigation Assistance
Sends updated availability
Mobile App & Digital Signage
Guides drivers to open spots
Driver Finds Parking Easily
Confirms parking occupancy
System Updates Availability

Fig. 3 AI-driven smart parking workflow for predictive and dynamic allocation

8 Future Trends and Research Directions

As smart cities develop, smart parking solutions will keep progressing alongside new technologies like self-driving cars, AI-enhanced traffic management, and advanced VANET frameworks [20]. These advancements will influence the future of city transportation by improving efficiency, minimizing congestion, and encouraging sustainability. This part examines the major trends and research paths that will propel the upcoming stage of smart parking solutions.

8.1 Incorporation of Self-driving Cars in Intelligent Parking

Upcoming Direction: The implementation of autonomous vehicles (AVs) will transform smart parking by facilitating:

(a) **Self-Parking Features**: Autonomous vehicles will independently find open spots without any driver input.
(b) **Enhanced Space Efficiency**: Autonomous vehicles can fit into smaller parking spots with reduced gaps, boosting total parking availability.
(c) **Decreased Traffic Congestion**: AVs will interact with intelligent parking systems to eliminate unnecessary searching times.

Research Avenues:

(a) **Enhanced Sensor Integration for Autonomous Vehicle Parking**: Creating AI-driven multi-sensor technologies (LiDAR, cameras, ultrasonic) for accurate self-parking [4].
(b) **Incorporation of V2X Communication for Autonomous Vehicle Parking Management**: Facilitating instantaneous collaboration among AVs, parking facilities, and traffic lights.
(c) **Automated Valet Parking Systems**: Investigating robotic parking assistants and AI-powered parking centers to oversee AV parking autonomously.

8.2 AI-Enhanced Traffic Management Associated with Parking

Upcoming Trend: Traffic management systems powered by AI will work in conjunction with smart parking solutions to facilitate smooth vehicle flow throughout urban areas. Major developments encompass:

(a) **Real-Time Traffic Forecasting**: AI systems will anticipate traffic levels and guide vehicles to parking spots with lower congestion.
(b) **Dynamic Parking Demand Regulation**: AI will assign parking spots according to anticipated peak times, unique events, and vehicle spread [14].
(c) **Traffic Signal Optimization**: AI will align intelligent traffic signals with parking space availability to avoid congestion around parking areas.

Areas of Investigation:

(a) **Reinforcement Learning for Instant Traffic Improvement**: Developing AI models to forecast traffic trends and modify parking distribution in real time.
(b) **AI-Driven Multi-Modal Transport Planning**: Combining intelligent parking solutions with public transport networks to lessen reliance on personal cars.
(c) **Automated Incident Identification and Reaction**: AI-based monitoring to detect and alleviate parking-related traffic jams or roadway blockages.

8.3 Possible Developments in Parking Solutions Based on VANET

Upcoming Direction: Parking systems based on VANET will develop alongside next-generation networking technologies, facilitating ultra-quick, low-latency communication between vehicles and infrastructure [46]. Anticipated progressions encompass:

(a) **VANET Networks with 5G Support**: Enhancing immediate data transfer and minimizing delay in parking management.
(b) **Distributed Parking Information Exchange**: Utilizing blockchain and VANETs for secure, instantaneous data sharing.
(c) **AI-Driven Routing Algorithms at the Edge**: Utilizing AI at network peripheries for immediate parking suggestions and route enhancements.

Investigation Avenues:

(a) **Combining AI with VANET-Based Routing Protocols**: Creating AI-driven decision-making for the best allocation of parking spaces.
(b) **Independent Decision-Making for Parking Bookings**: Cars utilizing V2V and V2I communication to reserve and find parking spaces [2].
(c) **Hybrid VANET-Cloud Parking Solutions**: Merging edge computing with cloud-based AI algorithms for quicker, more adaptable intelligent parking networks.

9 Conclusion

The swift urban growth and rising vehicle count in urban areas have rendered smart parking solutions essential for sustainable city mobility. This study has examined how AI, IOT, and VANETs are revolutionizing parking management by boosting efficiency, decreasing congestion, and improving the experience for drivers.

Main Takeaways are:

(a) **AI-Powered Enhancement**: Intelligent parking utilizes machine learning and predictive analysis for immediate space distribution and demand prediction.
(b) **IOT-Based Monitoring**: Intelligent sensors and cloud platforms offer real-time information on parking space availability, minimizing search durations.
(c) **VANET-Enabled Communication**: Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) exchanges enhance navigation and parking booking.
(d) **Technological Facilitators**: Edge computing, 5G networks, and blockchain improve data protection, communication rates, and transaction clarity.
(e) **Obstacles and Remedies**: Major hurdles like data protection, network scalability, interoperability, and financial limitations necessitate strategic methods, including blockchain incorporation, standardization, and collaboration between public and private sectors.

(f) **Future Trends**: Developments in self-parking technologies, AI-enhanced traffic management, and advanced VANETs will keep transforming parking solutions.

Consequences for City Planners and Decision-Makers: To successfully implement smart parking, urban planners and policymakers need to:

(a) **Implement Smart City Approaches**: Merge parking solutions with wider intelligent transportation systems (ITS) for effortless mobility.
(b) **Promote Cooperation Between Public and Private Sectors**: Collaborate with tech companies, startups, and the automotive sector to speed up implementation.
(c) **Enhance Digital Infrastructure**: Implement 5G, IOT, and AI-powered systems to boost scalability and manage parking in real time.
(d) **Encourage Sustainable Transport**: Introduce rewards for electric vehicle parking, flexible pricing strategies, and integrated transport options.

Concluding Insights on the Future of Intelligent Parking as urban areas expand, intelligent parking solutions will be essential in enhancing city spaces, alleviating traffic congestion, and promoting sustainability.

The combination of AI, IOT, and VANETs will facilitate completely automated and self-sufficient parking systems, allowing vehicles to interact effortlessly with infrastructure for optimal space usage. In the future, studies in AI-driven decision-making, immediate traffic management, and distributed parking systems will continue to transform smart mobility.

By adopting these advancements, cities can improve urban life, reduce ecological effects, and provide a smooth, technology-enhanced parking experience for everyone.

References

1. Abuashour, A., Kadoch, M.: Performance improvement of cluster-based routing protocol in VANET. IEEE Access **5**, 15354–15371 (2017). https://doi.org/10.1109/ACCESS.2017.2733380
2. Aliedani, A., Loke, S.W.: Cooperative car parking using vehicle-to-vehicle communication: An agent-based analysis. Comput. Environ. Urban Syst. **77**, 101256 (2019). https://doi.org/10.1016/j.compenvurbsys.2018.06.002
3. Al-Turjman, F., Malekloo, A.: Smart parking in IOT-enabled cities: A survey. Sustain. Cities Soc. **49**, 101608 (2019). https://doi.org/10.1016/j.scs.2019.101608
4. Avoci, U.M., Marco, C., Antonio, P., Consolatina, L.: Enhanced sensor coverage for autonomous vehicles with a preliminary integration of fault detection scheme. Measurement: Sensors **18**, 100355 (2021). https://doi.org/10.1016/j.measen.2021.100355
5. Balzano, W., Vitale, F.: DiG-Park: A smart parking availability searching method using V2V/V2I and DGP-class problem. In: 2017 31st International Conference on Advanced Information Networking and Applications Workshops (WAINA), pp. 698–703 (2017). https://doi.org/10.1109/WAINA.2017.104
6. Chintalapati, B., Precht, A., Hanra, S., Laufer, R., Liwicki, M., Eickhoff, J.: Opportunities and challenges of on-board AI-based image recognition for small satellite Earth observation missions. Adv. Space Res. (2024). https://doi.org/10.1016/j.asr.2024.03.053

7. Deshmukh, R., et al.: Smart Digital Transformation: A Sustainable Path to Achieving the SDGs and a Green Net Zero Economy. IGI Global, pp. 241–276. eISBN 9798369365342 (2024a). https://doi.org/10.4018/979-8-3693-6532-8.ch011
8. Deshmukh, R., et al.: E-Governance and Digital Innovation—Indian Perspective. Lecture Notes in Networks and Systems, vol. 946. Springer, (pp 199–222). (eISBN 9781003440901) (2024b). https://doi.org/10.1007/978-981-97-1323-3-17
9. Dimitrakopoulos, G., Tsakanikas, A., PanagIOTopoulos, E.: Latest communication advances for autonomous vehicles. In: Autonomous Vehicles, pp. 33–43. Elsevier (2021). https://doi.org/10.1016/B978-0-323-90137-6.00005-9
10. Du, Z., Lin, B.: Changes in automobile energy consumption during urbanization: Evidence from 279 cities in China. Energy Policy **132**, 309–317 (2019). https://doi.org/10.1016/j.enpol.2019.05.050
11. E., L., & M., P. (2024). Efficient parking: A smart system for optimized urban mobility using IOT. J. Innov. Technol. **2024**(1). https://doi.org/10.61453/joit.v2024no40
12. Elassy, M., Al-Hattab, M., Takruri, M., Badawi, S.: Intelligent transportation systems for sustainable smart cities. Transp. Eng. **16**, 100252 (2024). https://doi.org/10.1016/j.treng.2024.100252
13. Elfaki, A.O., Messoudi, W., Bushnag, A., Abuzneid, S., Alhmiedat, T.: A smart real-time parking control and monitoring system. Sensors **23**(24), 9741 (2023). https://doi.org/10.3390/s23249741
14. Errousso, H., El Ouadi, J., Abdellaoui Alaoui, E.A., Benhadou, S.: Dynamic parking space allocation at urban scale: Problem formulation and resolution. J. King Saud Univ. Comput. Inf. Sci. **34**(10), 9576–9590 (2022). https://doi.org/10.1016/j.jksuci.2021.11.011
15. Faheem, M.S.A., Khan, G.M., Rahman, M., Zafar, H.: A survey of intelligent car parking system. J. Appl. Res. Technol. **11**(5), 714–726 (2013).https://doi.org/10.1016/S1665-6423(13)71580-3
16. Fahim, A., Hasan, M., Chowdhury, M.A.: Smart parking systems: Comprehensive review based on various aspects. Heliyon **7**(5), e07050 (2021). https://doi.org/10.1016/j.heliyon.2021.e07050
17. Fontes, C., Hohma, E., Corrigan, C.C., Lütge, C.: AI-powered public surveillance systems: Why we (might) need them and how we want them. Technol. Soc. **71**, 102137 (2022). https://doi.org/10.1016/j.techsoc.2022.102137
18. Gupta, N., Prakash, A., Tripathi, R.: Medium access control protocols for safety applications in vehicular ad-hoc network: A classification and comprehensive survey. Veh. Commun. **2**(4), 223–237 (2015). https://doi.org/10.1016/j.vehcom.2015.10.001
19. Hossain, Md.D., Sultana, T., Akhter, S., Hossain, M.I., Thu, N.T., Huynh, L.N.T., Lee, G.-W., Huh, E.-N.: The role of microservice approach in edge computing: Opportunities, challenges, and research directions. ICT Express **9**(6), 1162–1182 (2023). https://doi.org/10.1016/j.icte.2023.06.006
20. Jagatheesaperumal, S.K., Bibri, S.E., Huang, J., Rajapandian, J., Parthiban, B.: Artificial intelligence of things for smart cities: Advanced solutions for enhancing transportation safety. Computat. Urban Sci. **4**(1), 10 (2024). https://doi.org/10.1007/s43762-024-00120-6
21. Jadhav, B., et al.: Role of human-centered design and technologies in smart transportation system. Lecture Notes in Intelligent Transportation & Infrastructure ((LNITI)), Springer, pp 133–152. eISBN 978-3-031-72617-0 (2025a). https://doi.org/10.1007/978-3-031-72617-0_8
22. Jadhav, B., et al.: Beyond the horizon: Exploring the future of artificial intelligence (AI) powered sustainable mobility in public transportation system. Lecture Notes in Intelligent Transportation and Infrastructure ((LNITI)), pp. 397–409. Springer (eISBN 978-3-031-72617-0) (2025b). https://doi.org/10.1007/978-3-031-72617-0_21
23. Jadhav, B., et al.: Leveraging Blockchain and Smart Contracts for Gig Payments, pp. 161–173. Taylor & Francis (eISBN 9781032720104) (2024). https://doi.org/10.1201/9781032720104-11
24. Joshua, H.J., Herwindiati, D.E.: Automatic license plate recognition for parking system using convolutional neural networks. In: 2020 International Conference on Information Management and Technology (ICIMTech), pp. 71–74 (2020).https://doi.org/10.1109/ICIMTech50083.2020.9211173

25. Keramati Feyz Abadi, M.M., Liu, C., Zhang, M., Hu, Y., Xu, Y.: Leveraging AI for energy-efficient manufacturing systems: Review and future prospectives. J. Manuf. Syst. **78**, 153–177 (2025).https://doi.org/10.1016/j.jmsy.2024.11.017
26. Karani, G., et al.: How Traditional Banks Adapt to the Fintech Revolution in Banking and Finance Sector, pp. 214–225. Taylor & Francis (2025). (e-ISBN 978–100350194–7). https://doi.org/10.4324/9781003501947-13
27. Kharche, A., Badholia, S., & Upadhyay, R.K.: Implementation of blockchain technology in integrated IOT networks for constructing scalable ITS systems in India. Blockchain Res. Appl. **5**(2), 100188 (2024). https://doi.org/10.1016/j.bcra.2024.100188
28. Khang, A., et al.: AI-Centric Modelling & Analytics: Concepts, Technologies, & Applications. Taylor & Francis, (eISBN 9781003400110) (2023). https://doi.org/10.1201/9781003400110
29. Khang, A. et al.: Synergy of AI and Fintech in the Digital Gig Economy. Taylor & Francis, eISBN 9781032720104 (2024).https://doi.org/10.1201/9781032720104
30. Muhammad, M., Safdar, G.A.: 5G-based V2V broadcast communications: A security perspective. Array **11**, 100084 (2021). https://doi.org/10.1016/j.array.2021.100084
31. Ohanu, C.P., Rufai, S.A., Oluchi, U.C.: A comprehensive review of recent developments in smart grid through renewable energy resources integration. Heliyon **10**(3), e25705 (2024). https://doi.org/10.1016/j.heliyon.2024.e25705
32. Okonta, D.E., Vukovic, V.: Smart cities software applications for sustainability and resilience. Heliyon **10**(12), e32654 (2024). https://doi.org/10.1016/j.heliyon.2024.e32654
33. Parmar, J., Das, P., Dave, S.M.: A machine learning approach for modelling parking duration in urban land-use. Physica A **572**, 125873 (2021). https://doi.org/10.1016/j.physa.2021.125873
34. Parvez Farazi, N., Zou, B., Ahamed, T., Barua, L.: Deep reinforcement learning in transportation research: A review. Transp. Res. Interdisc. Perspect. **11**, 100425 (2021). https://doi.org/10.1016/j.trip.2021.100425
35. Pilz, C.: Vehicle communication platform to anything-VehicleCAPTAIN. In: Karner, M., Peltola, J., Jerne, M., Kulas, L., Priller, P. (Eds.), Intelligent Secure Trustable Things, vol. 1147, pp. 185–199. Springer Nature, Switzerland (2024). https://doi.org/10.1007/978-3-031-54049-3_11
36. Pilz, D., Schwerdfeger, S., Boysen, N.: Make or break: Coordinated assignment of parking space for breaks and rest periods in long-haul trucking. Transp. Res. Part B Methodol. **164**, 45–64 (2022). https://doi.org/10.1016/j.trb.2022.08.002
37. Provoost, J.C., Kamilaris, A., Wismans, L.J.J., Van Der Drift, S.J., Van Keulen, M.: Predicting parking occupancy via machine learning in the web of things. Internet of Things **12**, 100301 (2020). https://doi.org/10.1016/j.IOT.2020.100301
38. Rai, H.M., Shukla, K.K., Tightiz, L., Padmanaban, S.: Enhancing data security and privacy in energy applications: Integrating IOT and blockchain technologies. Heliyon **10**(19), e38917 (2024). https://doi.org/10.1016/j.heliyon.2024.e38917
39. Raj, A., Shetty, S.D.: Smart parking systems technologies, tools, and challenges for implementing in a smart city environment: A survey based on IOT & ML perspective. Int. J. Mach. Learn. Cybern. **15**(7), 2673–2694 (2024). https://doi.org/10.1007/s13042-023-02056-5
40. Rathore, M.M., Paul, A., Hong, W.-H., Seo, H., Awan, I., Saeed, S.: Exploiting IOT and big data analytics: Defining smart digital city using real-time urban data. Sustain. Cities Soc. **40**, 600–610 (2018). https://doi.org/10.1016/j.scs.2017.12.022
41. Rocco, G., Pipino, C., Pagano, C.: An overview of urban mobility: Revolutionizing with innovative smart parking systems. Sustainability **15**(17), 13174 (2023). https://doi.org/10.3390/su151713174
42. Singh, S.K., Pan, Y., Park, J.H.: Blockchain-enabled secure framework for energy-efficient smart parking in sustainable city environment. Sustain. Cities Soc. **76**, 103364 (2022). https://doi.org/10.1016/j.scs.2021.103364
43. Soori, M., Arezoo, B., Dastres, R.: Artificial intelligence, machine learning and deep learning in advanced robotics, a review. Cognit. Robot. **3**, 54–70 (2023). https://doi.org/10.1016/j.cogr.2023.04.001

44. Sayyed, M., et al.: AI-Centric Applications in Data Privacy and Cybersecurity, pp. 339–352. Taylor & Francis. (eISBN 9781003440901) (2024). https://doi.org/10.1201/9781003440901-21
45. Ul Haque, H.M., Zulfiqar, H., Khan, S.U., Ul Haque, M.: Context-aware parking systems in urban areas: A survey and early experiments. In: Cong Vinh, P., Alagar, V., (Eds.), Context-Aware Systems and Applications, and Nature of Computation and Communication, vol. 266, pp. 25–35. Springer International Publishing (2019). https://doi.org/10.1007/978-3-030-06152-4_3
46. Vahdat-Nejad, H., Ramazani, A., Mohammadi, T., Mansoor, W.: A survey on context-aware vehicular network applications. Veh. Commun. **3**, 43–57 (2016). https://doi.org/10.1016/j.vehcom.2016.01.002
47. Yang, H., Pu, C., Wu, J., Wu, Y., Xia, Y.: Enhancing OLSR protocol in VANETs with multi-objective particle swarm optimization. Physica A **614**, 128570 (2023). https://doi.org/10.1016/j.physa.2023.128570
48. Yin, Y., Wang, X., Wang, H., Lu, B.: Application of edge computing and IOT technology in supply chain finance. Alex. Eng. J. **108**, 754–763 (2024). https://doi.org/10.1016/j.aej.2024.09.016
49. Zhang, X., Pitera, K., Wang, Y.: Parking reservation techniques: A review of research topics, considerations, and optimization methods. J. Traff. Transp. Eng. (English Edition) **10**(6), 1099–1117 (2023). https://doi.org/10.1016/j.jtte.2023.07.009

Intelligent VANET for Smart Cities and Their Security Challenges

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Abstract Intelligent integration of Vehicular Ad-hoc Networks (VANETs) provides improved quality of life for urban dwellers. Ecosystems for transportation give rapid evolution in a smart environment for both dynamic and linked scenarios of various vehicles utilizing real-time data gathered from the infrastructure area. Utilizing these real-time data lays the groundwork for road safety, sustainable mobility behaviors, and enhancing the traffic flow in the center of the urban regions. Modern algorithms and technology have the potential to usher in a slew of game-changing innovations that will enhance transportation efficiency and the quality of life for drivers. A promising future is one in which vehicles equipped with collision avoidance technology enable them to share data. The process of VANET integration in urban regions responds to the vehicles to provide adaptive speed adjustments in response to current traffic environments, road conditions, patterns, and collision warnings to avoid possible hazards for the drivers through VANETs. The scenario of this integration of VANETs in city centers helps to make roads safer for drivers, avoiding the negative effects of emissions from vehicles to the environment, and reducing traffic congestion. This VANET integration tackles complex urban transportation problems, makes the city people's lives easier through transit, and clever city trip planners for

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the people. With this method, we can focus on the new programs and regulations that will help cities grow more efficiently.

Keywords Machine learning · VANET · Smart cities · Edge computing

1 Introduction to Intelligent VANETS and Smart Cities

The seamless integration of VANETs for smart cities improves sustainable development for people who live in urban regions. The integration of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) can lessen the congestion caused by vehicles, prevent accidents, and optimize the road plan for city riders. Advancements in these integrations contribute to a more efficient urban environment but also promote safer travel for all the road users. Looking into how Intelligent Transportation Systems (ITS) can be built into city infrastructure is a very important part of working together to understand and set up VANETs in smart cities. Using new technologies is a big part of the latest innovative solutions for ITS that allow preventative measures. Real-time data from various vehicles can create predictive models, identifying potential accident sites, reducing risks, and enhancing community safety. Therefore, developing advanced solutions to improve road safety remains a critical priority within smart city frameworks. The demand for modern urban life requires modern, innovative technology in the smart city environment.

Specifically, intelligent VANETs are a crucial technology that offers numerous benefits for managing urban mobility among residents of smart cities. Intelligent VANETs facilitate communication between vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) in dynamic interactions. This collaborative ecosystem shares vital information like traffic conditions, road conditions, hazards, and optimal pathways. Vehicles can communicate the speed and direction information from one to another. This information sharing in real-time reduces the risk of collision among vehicles, also leads to more synchronized traffic flows, and reduces the congestion on road transport.

The future of urban development will be built on a strong foundation for safer, smarter, and more sustainable transportation in smart cities. It brings significant advancements in road safety while laying the groundwork for further improvements in intelligent urban transportation networks. Systems are being implemented to detect driver activities such as drowsy driving, speeding, and alcohol consumption. Light Fidelity (Li-Fi)-enabled vehicles provide assistance to prevent accidents by identifying the listed activities in Smart City vehicle-to-infrastructure (V2I) communication. Artificial Intelligence (AI) and IoT connectivity are revolutionizing the future of transportation, ensuring safety and more secure mobility in the smart city.

1.1 VANET Network

The field of VANETs is an extensive category of processes in smart cities. The participating vehicles in the VANET region cover around 100–300 m distance in urban scenarios. Whereas, on highways, the wireless transmission range is around 1000 m. The fundamental feature of VANETs is the ability for automobiles to speak to one another and establish communication with infrastructure. Smart cities can easily benefit from the sharing of collected data from the Internet of Vehicles (IoV) ecosystem, which includes vehicles, roads, infrastructure, buildings, and more. The unique characteristics of VANETs are the communication medium used, computing capabilities, mobility, storage, etc.

Vehicles should have their own identities to ensure strong security and privacy in VANETs. This will improve security by preventing unauthorized access and protecting privacy. We should also use efficient authentication to decrease the likelihood of tracking, profiling, or concealing real vehicle identities. We can efficiently perform authentication in VANETs by eliminating complex public key infrastructure and authorized certificates, resulting in faster and more scalable processes. VANETs allow vehicles to communicate through roadside equipment like surveillance cameras, ultrasonic sensors, and beacon transmitters in Intelligent Transportation Systems (ITS) for sustainable development in urban regions. Self-organizing mobile nodes that use this intelligent system to communicate information among the vehicles.

Event-driven and periodic are the two categories of safety applications in VANETs. VANETs implement broadcast-type communication. At regular intervals, each node transmits the safety message from one vehicle to another vehicle. During emergencies, only event-driven safety applications transmit the safety message among the vehicles. One node broadcasts the safety message through either one-hop or multi-hop messages to all other nodes within the communication range. The classification safety messages are categorized as classes 1, 2, and 3. Class 1 and 2 are under event-driven safety application, and class 3 is for periodic safety message application. Class 1 and 2 provide the critical safety messages for life-critical safety, intersection collision avoidance, emergency braking avoidance, safety warning, transit vehicle signal, and cooperative collision warning. Class 3 safety messages include vehicle status reporting, work zone warnings, and road hazard warnings.

1.2 Smart Cities

The complicated problems encountered in the ever-increasing population lead to deploying the smart cities concept in the urban region. Well-advanced technological impacts in the urban scenario led to sustainable development in a particular region. The primary objective of smart cities is to improve people's quality of life through innovative urban processes. This infrastructure provides optimized resource allocation, better decision-making abilities, and increasing information exchange service among end nodes. The goals are accomplished through a variety of fields and projects, including smart healthcare, smart buildings, smart mobility, smart energy management, and smart governance.

The robust digital infrastructure developed in the smart cities supports collecting, storing, and analyzing information from diverse nodes. For this infrastructure, we need seamless integration of urban systems with sensors, IoT devices, and broadcast communication. Smart cities prioritize the people-centric approach to emphasize the living standards of people in the urban region. The main pillar of sustainability in smart cities is to minimize the environmental impact and optimize the resources allocated.

2 Machine Learning Algorithms for VANETS

Machine learning algorithms are designed to analyze data, learn from it, and make predictions or decisions without being explicitly programmed for specific tasks. They can be categorized into various types, including supervised learning, unsupervised learning, and reinforcement learning. Each category has its unique applications and benefits, which can significantly enhance our capabilities in data analysis and decision-making. Table 1 represents the comparative analysis of various machine learning algorithms and its uniqueness.

Table 1 A comparative analysis of algorithms for machine learning

Algorithms	High dimensional data	Fastness	Outliers	Memory	Scalability
K-nearest neighbors (KNN)	–			–	
Naive Bayes	*	*			*
Support vector machine (SVM)	*		*	*	
Linear regression			*		
K-means		*	–		*
Density-based spatial clustering of applications with noise (DBSCAN)	*	*	*		
Feed forward neural network (FFNN)	*	*		*	
Q learning	*	*			

3 Enhancing Autonomy in Smart Cities Through VANETS

VANET's play a critical role in enabling autonomous operations in smart cities. It improves the efficiency, mobility and urban safety by effectively connecting vehicles, pedestrians and infrastructure through wireless communication. It aids in dynamic traffic control for optimization of traffic flow. Vehicles may move in a speed based on the upcoming traffic which will result in reduction of traffic. VANET's share information about the nearby vehicles and pedestrians to the server, which may be used by other vehicles for traffic management. Emergency situations like accidents, weather conditions and disasters may be communicated to the other nodes which help in better handling of these conditions. Methods to find shortest and less traffic route may be implemented for energy conservation. Smart infrastructure like cameras, traffic lights, and smart street lights may be integrated with VANET for effective urban infrastructure support. Vehicles connected with parking management systems provide the nearest parking slots which aids in smart parking solutions. Data analysis and visualization may be performed with received data from traffic and smart cities to help in data driven planning of the city. Gaps in infrastructure and where to optimize in smart cities may be identified, analysed and implemented.

Mezher et al. [1] introduced a multimedia-based, multi-metric routing protocol designed for VANETs in smart cities, optimizing video transmission for reporting purposes. Prevention of accidents is a major goal of VANET. A short video may be recorded and to access point when an emergency like an accident happens. This helps the authorities to identify the level of accident and act accordingly. An efficient routing protocol multimedia multimetric map-aware routing protocol was developed for the purpose. Real maps with SUMO was used for signal transmission among the sender and receiver. The movement of the nodes and the presence of buildings in between are applied in the analysis. Periodic "hello" messages were continuously sent among vehicles, which helps in interpreting the distance to destination, the density of vehicles in an instant, trajectory, available bandwidth estimation, and the packet losses in the MAC layer for local feedback information.

The processes routing, signaling, evaluation of the measures, and forward decision were used for the smart city implementation using VANET. In future work, the authors aim to incorporate a game-theoretical approach into the 3MRP routing protocol. This approach involves forwarding some frames with a certain probability to the best neighboring vehicle while sending others to the second-best neighbor, ensuring balanced transmission.

Lee et al. [2] proposed an efficient and safe message authentication protocol for the Internet of Vehicles (IoV) in smart cities, named IoV-SMAP. VANET combined with IoT provides services with IoV. For the transmitted messages to be secure, a secure message authentication protocol was introduced. The message may suffer from offline guessing attacks, impersonation, and secret key disclosure. The proposed IoV-SMAP helps in overcoming these security issues and provides mutual authentication and anonymity. The session key security concept was proven using the Real or Random (ROR) model by a mathematical analysis. Automated Validation of Internet

Security Protocols and Application (AVISPA) was used for the protocol implementation. The proposed system included an initialization and registration process, which includes V2V, V2I registration, V2V, and V2I authentication. Formal security analysis by the ROR model and informal security analysis include impersonation attacks, replay, session key disclosure, smart card theft, man-in-the-middle attacks, anonymity, and mutual authentication. Thus the SMAP is more suitable for IoV environment because of this enhanced efficiency and security features.

Smart living, autonomous connected driving, public safety, connected and smart health may be achieved by having proper resources for ubiquitous communications, more storage capacity of data, powerful computing, high storage and intelligence capacities and immense sensing power. Chen et al. [3] proposed Vehicle as a Service (VAAS) which gives a path for smart cities and provides a good alternative for 5G. The paper provides insights on how to transform from traditional VANETs to VAAS. The author performed an extensive literature survey in terms of communication, storage, computing, intelligence, and sensing with respect to VAAS. The reasons for implementing VAAS include public safety, smart mobility, smart, connected health, and smart living. Updation required when we move from VANET to VAAS are in the perspectives of spectrum, computation and design.

Wajdy et al. [4] gave a physically secure lightweight, privacy-protective message verification protocol for VANET given smart cities. Smart cities which included certification revocation lists (CRL) and public key infrastructure suffered from time consumption because of the large size of CRL, and traceability attacks by using uninterrupted basic safety messages and extracting secret keys of the roadside parked vehicles by unauthorized persons. To address this issue, the authors introduced a secure message preservation protocol based on Physical Unclonable Function (PUF) secret sharing. The method protests message loss against memory leakage. The data's pairwise temporal secret keys may be designed with other data. The vehicles send a safe offset key by threshold secret sharing approach.

The system model assigns a trusted authority to enroll vehicles and roadside units, issuing secret keys to network entities. These units can securely communicate their coverage range with the authority over a wireless connection. Communication also is enabled among vehicles with their onboard units. The design goals include message authentication, integrity, physical protection, message confidentiality, untraceability, and resistance to security attacks. The algorithm 1 included retrieval, mutual authentication and key renewal phase, V2V authenticated secure message communication phase and V2V broadcast secure message transmission. Algorithm 2 includes broadcast encryption and the revocation mechanism phase.

The challenges and innovative approaches for a communication-based perspective on traffic management systems for smart cities were proposed by Djahel et al. [5]. A systematic review of the traffic management systems phases and application of smart cars and social media accurate fast traffic congestion detection and mitigation. The possibilities of smart transportation were analyzed. The requirements for the above are more efficient dealing with road emergencies, managing traffic of different sizes and characteristics, Improvement in road infrastructure and route planning, and evolution to new system slowly without disrupting the existing system.

VANETs are key enablers in the transition towards interconnected, fully autonomous smart cities. By improving traffic management, safety, and energy efficiency, they clear the path for cities that are most sustainable, intelligent, and livable. Through collaboration between technology, infrastructure, and governance, VANETs will continue to enhance the autonomy of smart cities.

4 Edge Computing and AI Integration in VANETS

VANETs require fast real-time data processing and security. Edge computing helps in message authentication under heavy traffic, improving the computing power. The devices that have initially gone through authentication procedures only may be allowed to join VANET. Without any compromise on user identity, the devices in VANET if they identify any non-trustworthy node, the same may be communicated to other nodes in the network, which will aid in the early identification of wrong data transmission.

Tahir et al. [6] proposed a cornerstone in the combination of 5G mm-wave and a dedicated short-range communication (DSRC) system for fast vehicular networks. The architecture is named CtCNet- HDRNN. The model enables seamless communication between vehicles in a connected environment. It utilizes an adaptive learning rate and built-in regularization in its advanced training process, ensuring accurate data fitting, strong generalization, and fast convergence. For these resource-constrained networks and energy conservation, a Sparse Deep Recurrent Neural Network (SDRNN) was implemented which aids in the reduction of complexity. mmWave technology provides high-speed communication capabilities, while Monte Carlo methods enable dynamic collision avoidance and efficient channel access management in vehicular networks. The approach facilitated a smart and safe transportation system.

AI-based trust-aware and privacy-preserving system (ATPS) was developed by Ting et al. [7] to improve privacy among vehicular communication and data collection quality in VANETs. The method includes partial ordering-based trust management (POTM) and a trajectory privacy-preserving method. The information is collected from top-ranked vehicles and drones were used for trust vehicular data providing. The data quality improved to 52.57% and the malicious vehicle participants reduced to 16.95%.

Every vehicle should have its dedicated hardware for networking, storage, and computation, enabling fast secure data transfer within vehicles in the network. Recently 5G network has been enabled in vehicles for seamless communication. Free space optical portion of the spectrum may be used for intra-vehicle data transmission. Edge computing helps in accommodating the future high demand for vehicle communication. The side unit works as a fog layer and makes decisions on which data to accept and reject and aids in reducing the traffic in the system.

5 Security and Privacy Issues in Intelligent VANET

Security is a major concern in Intelligent VANET as they are open-type communication networks. Due to the nature of unbound network size and the exchange of information at a higher frequency, it is prone to attacks. Security faces challenges based on different factors like authentication, authorization, Data integrity, confidentiality, privacy, and many more [8].

5.1 Security Challenges in VANET

In this section, the various security challenges are discussed

(i) **Based on Authorization and Authentication**

Authentication ensures and checks the identity of the units at the roadside and the units onboard. This permits communication between the entities. The authorization also checks whether the entity has access to the network information [9]. They are being implemented using cryptography, blockchain technology, or digital signatures. The following attacks are made under the category of authentication and authorization like vehicle and node impersonation, unauthorized access, and fake identity injection [10].

(ii) **Data Integrity and Confidentiality**

Data integrity imposes the correctness of the data and confidentiality ensures only the authenticated users to access the data with the help of encryption and decryption algorithms [11]. Importance should be given to integrity and confidentiality or else this will lead to issues like data tampering, and eavesdropping which discloses the vehicle data [12].

(iii) **Non-Repudiation**

An assurance that neither the sender (a vehicle or an infrastructure node) nor the recipient (a receiver) can deny conveying the message. This factor plays a major role due to the factors of safety accountability and fraud prevention. Digital signatures, certificate authority, and blockchain-based solutions are used to ensure nonrepudiation [8, 10].

(iv) **Availability**

One important consideration for VANET security is availability [9]. This guarantees that, despite flaws and attempts at denial of service attacks, all network resources will always be accessible. The major drawbacks in availability are data tampering, data jamming, and Denial of service (DOS)attacks. VANETs can be protected from these assaults with the help of cryptography and trust-based algorithms and protocols.

(v) **Privacy**

It is the protection of information that is exchanged between vehicles, and units at the roadside. The user data, location, and vehicle route information are to be protected from attackers. The attackers collect the data to build the traveller profile and alter the data and stalking on the user is done by location tracking. These issues can be avoided by adopting pseudonyms and identity-preserving privacy [8, 12, 13].

(vi) **Trust Management**

It refers to the assessment of the accuracy of information exchanged between vehicles and other nodes. This is important for safety and security applications like traffic warnings and collision avoidance because malicious intrusion may attempt to disseminate false information if it is not adequately verified through a trust mechanism, which frequently uses a reputation mechanism in which the vehicles gain trust from previous interactions and feedback from other nodes in the network.

In a Sybil attack [14, 15], the perpetrator creates many vehicle identities and disseminates false information around the network. In the instance of a Sybil attack, data is transmitted using a fabricated identity. This assault is executed from one OBU against other OBUs following authentication to obtain personal advantages. In black hole attack, is a type of routing attack in which a malicious node lures the victim's node within the network. Furthermore, it ensures data transmission by determining the most efficient route to the recipient node [16–18].

(vii) **Key Management**

They maintain the encryption and decryption keys for closed-loop communication between the nodes and the vehicles. The algorithm chosen should be strong enough or else the malicious attacker may hack into the cryptographic keys used by the network [19].

(viii) **Physical Layer Security**

It refers to defense against threats and attacks on the hardware and communication infrastructure at the network's physical layer. The major concern here is the node tampering and battery-draining attack. In node tampering the intruders gain access to the sensors on board through the data can be tampered. In battery battery-draining attack, the malicious sender transmits unwanted data continuously through which the battery is drained [13–18].

5.2 Privacy Challenge in VANET

Privacy is a major concern during the sensitive information sharing between the vehicles, nodes, and the units at the roadside. Malicious attackers plan to expose the information shared between the entities through which they can stalk the vehicle movement [20].

The following are the primary concerns in privacy in VANETs

(i) **Location Privacy**

Location-based services are widely needed for information regarding traffic congestion, collision avoidance, and navigation. Hence the Continuous car location data transfer may expose protected location data, making it possible to monitor the vehicle. Malevolent individuals follow a person's whereabouts or violate their privacy [21].

(ii) **Identity Privacy**

To maintain the confidentiality of the vehicle user, identity privacy makes use of the pseudonym to prevent the attacker from locating the location of the vehicle user [22].

(iii) **Communication Privacy**

The sender and the receiver maintain an anonymous identity and exchange information between the sender and receiver without disclosing private information. By providing access control, we can prevent the attacker from hacking the information [23].

(iv) **Data Compilation and Classification**

The vehicles within the location are formed in clusters and the data about the location and speed of the vehicle within the clusters are shared. This helps to improve the road safety. This allows the attacker to create a profile database about the vehicle user. This can be avoided by including cryptography techniques and other blockchain-based techniques [21, 22].

(v) **Replay Attack**

The attacker keeps track of the valid information transmitted between nodes within the cluster and they replay the valid information at a different instant of time and confuse the other nodes about the whereabouts of the vehicle [24, 25].

6 Case Studies and Real-World Applications

VANET network paves the way for drivers and passengers to use the transport system smoothly, safely, and more efficiently by focusing on safety, connectivity, and mobility for both public and private. Implementation of IoT enhances the proposal of advanced solutions for real-time monitoring of information related to co-existing vehicles in smart cities. This section deals with real-time case studies and the implementation of VANETs for smart cities.

In [26], new Social IoT (SIoT) which is an evolution of IoT, integrating connecting devices with networking principles analogous to human social networks is implemented to build a smart city in Cagliari, Italy (Fig. 1). The real-time data collection involves private and public vehicles, and in addition to that data from pedestrians to improve the living conditions and information of new directions. ML is implemented to process data from traffic lights. The vital components of the proposed architecture

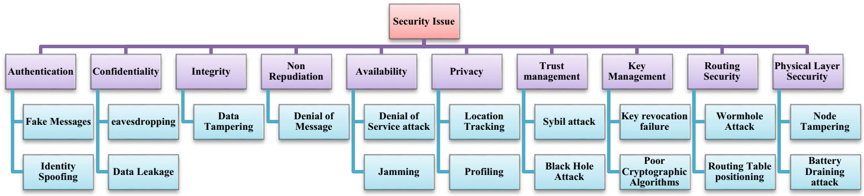
Security Issue
Authentication
Confidentiality
Integrity
Non Repudiation
Availability
Privacy
Trust management
Key Management
Routing Security
Physical Layer Seccurity
Fake Messages
Identity Spoofing
eavesdropping
Data Leakage
Data Tampering
Denial of Message
Denial of Service attack
Jamming
Location Tracking
Profiling
Sybil attack
Black Hole Attack
Key revocation failure
Poor Cryptographic Algorithms
Wormhole Attack
Routing Table positioning
Node Tampering
Battery Draining attack

Fig. 1 Categories of security issues and challenges in intelligent VANET

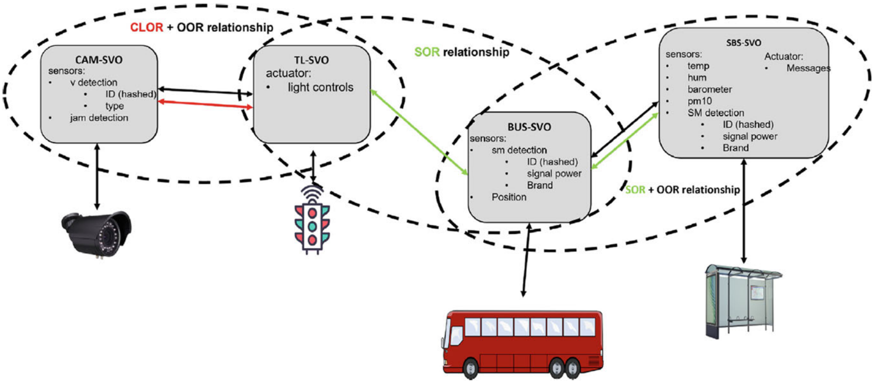
CLOR + OOR relationship
CAM-SVO
sensors:
v detection
ID (hashed)
type
jam detection
TL-SVO
actuator:
light controls
SOR relationship
SBS-SVO
sensors:
temp
hum
barometer
pm10
SM detection
ID (hashed)
signal power
Brand
Actuator:
Messages
BUS-SVO
sensors:
sm detection
ID (hashed)
signal power
Brand
Position
SOR + OOR relationship

Fig. 2 Social connections between social virtual objects (SVO) of the systems [26]

include mobility sensors, control units for crowds, Lysis complaint integration interoperability modules, and a platform for data analysis. The operation is performed in three levels, Level 1 comprises data acquisition from mobility sensors and crowd monitoring systems; Level 2 includes data anonymization and transmission to the cloud; and Level 3 deals with the management and storage of data as shown in Fig. 2.

The analysis of the proposed SIoT-based smart city was carried out by collecting data during five working days (Monday to Friday) for consecutive three months. The data collection was performed in three windows of various timings (8–10 am; 1–3 pm and 4–10 am when the workers return). The proposed system shows a 30% average gain in the distribution of vehicles in terms of traffic savings. A front-end user interface was developed to show the best route suitable for the data collected and the application can be trained by storing main destinations. The proposed system shows 20% betterment in comparison to previous works and shows a maximum 35% gain in the evening (8 pm) slot.

Figure 2 [26] shows a case study where the routing protocols of VANETs are compared in terms of efficiency in implementation in the city of Khartoum, Sudan. The three routing protocols considered are Dynamic Source Routing (DSR), Ad hoc On-Demand Distance Vector (AODV), and Destination Sequenced Distance Vector (DSDV). The evaluation was performed using the mobility model simulator, MOtor Vehicle Emission simulator (MOVE), and VANETs simulator Simulator for Urban

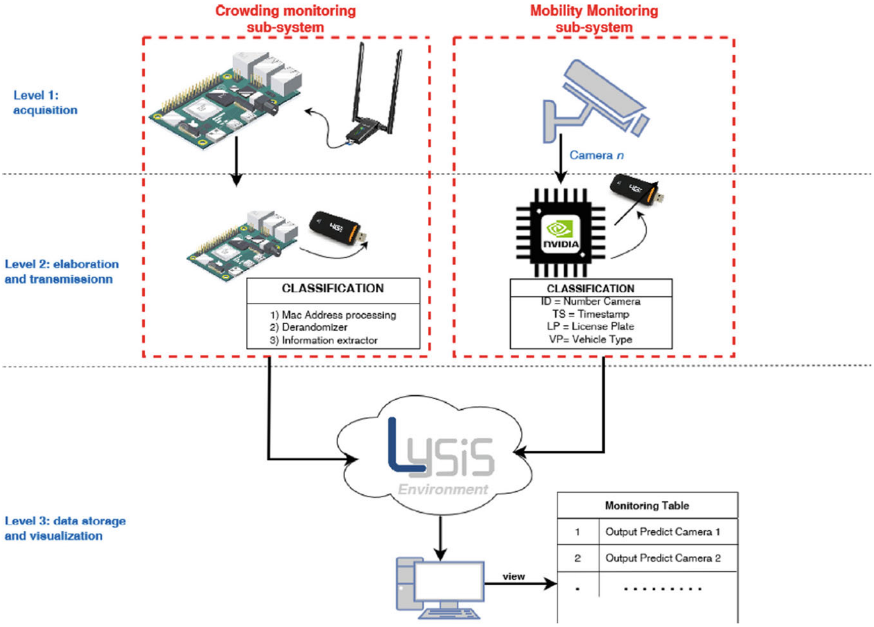
Crowding monitoring sub-system
Mobility Monitoring sub-system
Level 1: acquisition
Camera n
Level 2: elaboration and transmissionn
CLASSIFICATION
1) Mac Address processing
2) Derandomizer
3) Information extractor
CLASSIFICATION
ID = Number Camera
TS = Timestamp
LP = License Plate
VP= Vehicle Type
nVIDIA
Lysis Environment
Level 3: data storage and visualization
view
Monitoring Table
1 Output Predict Camera 1
2 Output Predict Camera 2
. ...

Fig. 3 Representation of monitoring system [26]

Mobility (SUMO). Figure 3 shows the methodology of generating traffic models and mobility, which describes the steps of a simulation study. Figure 4 shows the road topology of the Alriyadh region (Khartoum), created using map editors. Similarly, Reference [28] provides another case study for the evaluation of the VANET routing protocol on urban scenario.

In terms of average throughput when vehicles are increasing, DSDV shows poor throughput whereas AODV has an average throughput of 330.37 kbps when the number of vehicles is 130, and DSR, for 80 vehicles, displays an average throughput of 323.37 kbps.

DSDV has the maximum delay for increasing vehicles. DSR and AODV exhibit the minimum delay of 15.81 ms and 41.33 ms for 200 and 110 nodes, thus making DSR more suitable in terms of delay metric. When total energy consumed is measured, AODV and DSR show the highest consumed energy as 357 for 100 and 80 vehicles. In conclusion, reactive routing protocols, AODV, and DSR perform better for increasing vehicles.

An effective routing protocol for VANETs is the IEEE 802.11p protocol wireless data exchange is a need of the hour for better network Quality of Service (QoS). In [3] characteristics of various routing protocols like OLSR, AODV, and DSDV are determined for parameters like Packet Delivery Ratio (PDR), Packet Loss Ratio (PLR), and end-to-end delay using tools like SUMO and NS3. In terms of PDR, AODV and DSDV perform better than OLSR. DSDV shows an improvement of 28% from 18% for increasing nodes and 30% to 86% was achieved by AODV. The

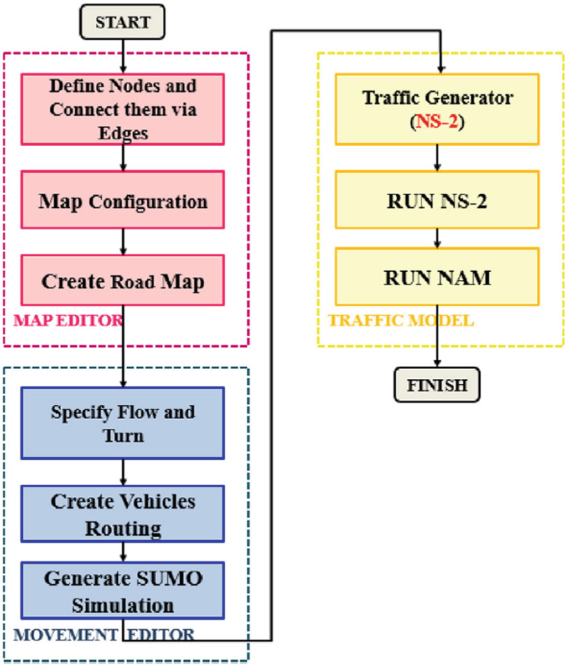
START
Define Nodes and Connect them via Edges
Map Configuration
Create Road Map
MAP EDITOR
Specify Flow and Turn
Create Vehicles Routing
Generate SUMO Simulation
MOVEMENT EDITOR
Traffic Generator (NS-2)
RUN NS-2
RUN NAM
TRAFFIC MODEL
FINISH

Fig. 4 Flow chart [27]

performance of OLSR degrades to 55% from 85% for 250 nodes. OLSR shows an increase in PLR value from 14 to 44%, depicting its low performance. DSDV and AODV show a reduction in the PLR value to 71% from 81 and 13% from 69% respectively. AODV performance is best in terms of PLR. Whereas, in terms of end-to-end delay, AODV has a delay of 16,782.6 s DSDV has a 735.2 s delay and OLSR has a 367 s delay. Thus, AODV has the best performance in terms of PDR and PLR, but OLSR is best in terms of delay. Figure 5 shows the methodology steps.

Reference [29] proposes a Multi-objective unmanned aerial vehicle (UAV) assisted roadside unit (RSU) deployment (MOURD) for using UAV for VANETs. MOURAD works by placing RSU in high-traffic areas and dispatching UAVs in low-traffic segments to increase the coverage of the network and minimize the latency in the network. It was effectively studied for the roads of Delhi, India, and outperforms other deployment approaches by 6.23% in terms of latency, 15.67% in terms of throughput 7.42% in terms of connection time with vehicles, and 13.9% in terms of PDR. Figure 6 shows the simulation steps for PDR, PLR and E2E delay computation.

7 Future Directions and Research Opportunities

For increasing the development of future VANETs in smart cities that are more sustainable, research directions for the future are summarized as follows [30, 31].

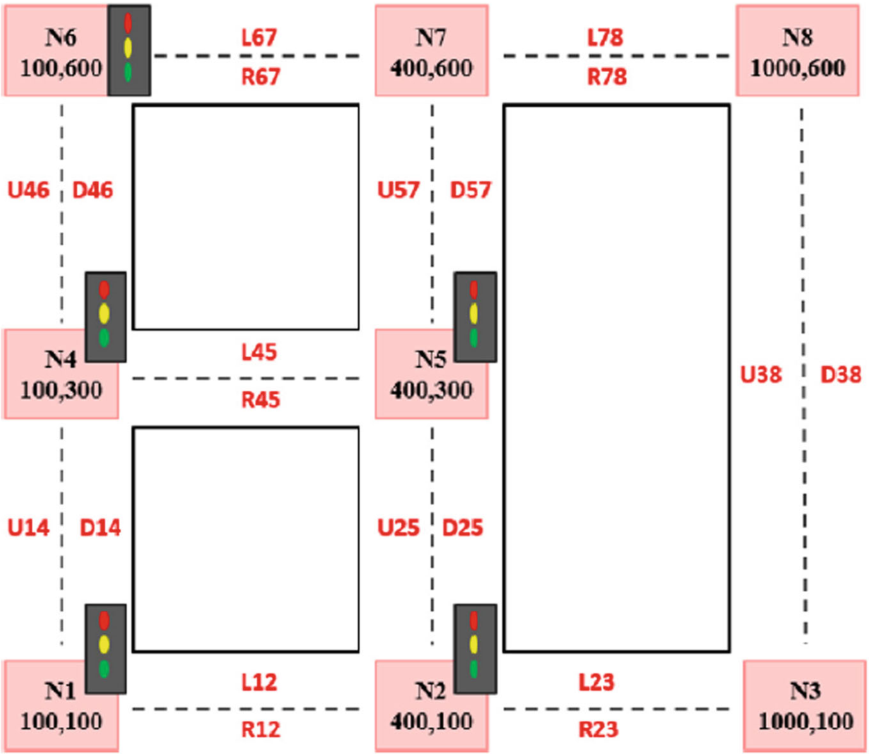
N6
100,600
L67
R67
N7
400,600
L78
R78
N8
1000,600
U46
D46
U57
D57
N4
100,300
L45
R45
N5
400,300
U38
D38
U14
D14
U25
D25
N1
100,100
L12
R12
N2
400,100
L23
R23
N3
1000,100

Fig. 5 Road map [27]

- Connectivity—Synchronized and reliable connectivity is in high demand for future VANETs to enable fast and continuous exchange of data and to avoid problems in propagation through channels.
- Implementation of Augmented Reality (AR)—AR technology can be used to assist drivers with a real-world image of nearby traffic, vehicles and pedestrians.
- Security—Encryption of data should be focused more as through nodes, clouds can be easily accessed.
- Latency—Low latency is a primary goal for future VANETs.
- Bandwidth—High bandwidth is in demand for video streaming and other entertainment activities. Updated navigation systems and 3D maps require more bandwidth.
- Information-Centric Networking (ICN)—ICN-based solutions can be envisioned in different architectures along with a focus on network scalability, device mobility, and access to information.
- Developing accurate prediction models—Accurate and efficient prediction models help in mobility management by reducing the communication challenges.
- Mobile Edge Computing—Pairing of edge computing with SDN can reduce latency.

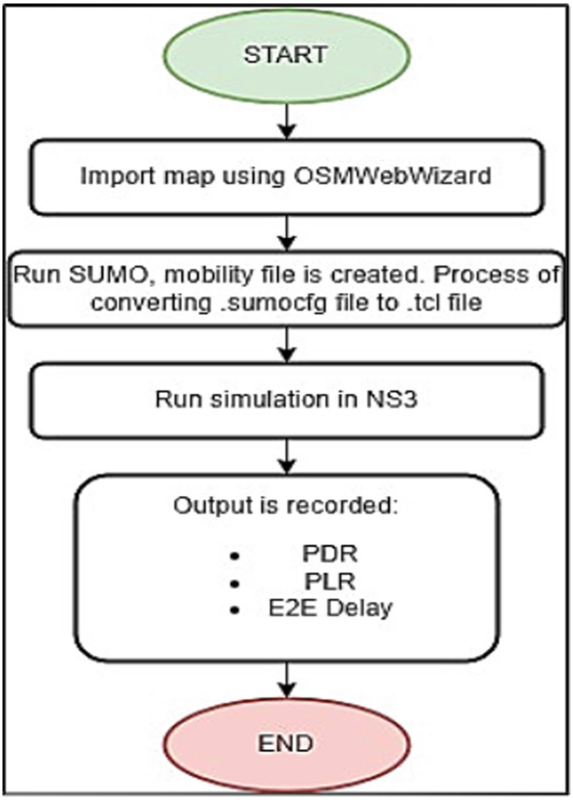
START
Import map using OSMWebWizard
Run SUMO, mobility file is created. Process of converting .sumocfg file to .tcl file
Run simulation in NS3
Output is recorded:
• PDR
• PLR
• E2E Delay
END

Fig. 6 Simulation methodology [29]

- Content Catching—It includes cooperative caching and prefetching. It can be used to send and store non-requested items.

References

1. Mezher, A.M., Igartua, M.A.: Multimedia multimetric map-aware routing protocol to send video-reporting messages over VANETs in smart cities. IEEE Trans. Veh. Technol. **66**(12), 10611–10625 (2017). https://doi.org/10.1109/TVT.2017.2715719
2. Yu, S., Lee, J., Park, K., Das, A.K., Park, Y.: IoV-SMAP: Secure and Efficient message authentication protocol for IoV in smart city environment. IEEE Access **8**, 167875–167886 (2020). https://doi.org/10.1109/ACCESS.2020.3022778
3. Chen, X., et al.: Vehicle as a service (VaaS): Leverage vehicles to build service networks and capabilities for smart cities. IEEE Commun. Surv. Tutorials **26**(3), 2048–2081, thirdquarter (2024). https://doi.org/10.1109/COMST.2024.3370169
4. Othman, W., Fuyou, M., Xue, K., Hawbani, A.: Physically secure lightweight and privacy-preserving message authentication protocol for VANET in smart city. IEEE Trans. Veh. Technol. **70**(12), 12902–12917 (2021). https://doi.org/10.1109/TVT.2021.3121449

5. Djahel, S., Doolan, R., Muntean, G.-M., Murphy, J.: A communications-oriented perspective on traffic management systems for smart cities: Challenges and innovative approaches. IEEE Commun. Surv. Tutorials **17**(1), 125–151, Firstquarter (2015). https://doi.org/10.1109/COMST.2014.2339817
6. Ahmed, T.H., Tiang, J.J., Mahmud, A., Gwo-Chin, C., Do, D.-T.: Proposed CtCNet-HDRNN: A cornerstone in the integration of 5G mmWave and DSRC for high-speed vehicular networks. IEEE Access **11**, 126482–126506 (2023). https://doi.org/10.1109/ACCESS.2023.3329872
7. Li, T., Xie, S., Zeng, Z., Dong, M., Liu, A.: ATPS: An AI based trust-aware and privacy-preserving system for vehicle managements in sustainable VANETs. IEEE Trans. Intell. Transp. Syst. **23**(10), 19837–19851 (2022). https://doi.org/10.1109/TITS.2022.3193369
8. Abdulkader, Z.A., Abdullah, A., Abdullah, M.T., Zukarnain, Z.A.: Vehicular ad hoc networks and security issues: Survey. Mod. Appl. Sci. **11**(5), 30 (2017)
9. Sheikh, M.S., Liang, J., Wang, W.: Security and privacy in vehicular ad hoc network and vehicle cloud computing: a survey. Wirel. Commun. Mob. Comput. **2020**(1), 5129620 (2020)
10. Agarwal, P.: Technical review on different applications, challenges and security in VANET. J. Multim. Technol. Recent Adv. **4**(3), 21–30 (2017)
11. Afzal, Z., & Kumar, M.: Security of vehicular Ad-hoc networks (VANET): A survey. In: Journal of Physics: Conference Series, vol. 1427, no. 1, p. 012015. IOP Publishing (2020)
12. Caballero-Gil, P., Wang, X.: Security issues in vehicular ad hoc networks. Mobile Ad-Hoc Networks: Applications, pp. 67–88 (2011)
13. Tripathi, V.K., Venkaeswari, S.: Secure communication with privacy preservation in VANET-using multilingual translation. In: 2015 Global Conference on Communication Technologies (GCCT), pp. 125–127. IEEE (2015)
14. Irshad, A., Usman, M., Chaudhry, S.A., Naqvi, H., Shafiq, M.: A provably secure and efficient authenticated key agreement scheme for energy internet-based vehicle-to-grid technology framework. IEEE Trans. Ind. Appl. **56**(4), 4425–4435 (2020)
15. Rahbari, M., Jamali, M.A.J.: Efficient detection of Sybil attack based on cryptography in VANET (2011). arXiv preprint arXiv:1112.2257
16. Sakiz, F., Sen, S.: A survey of attacks and detection mechanisms on intelligent transportation systems: VANETs and IoV. Ad Hoc Netw. **61**, 33–50 (2017)
17. Dhyani, I., Goel, N., Sharma, G., Mallick, B.: A reliable tactic for detecting black hole attack in vehicular ad hoc networks. In: Advances in Computer and Computational Sciences: Proceedings of ICCCCS 2016, vol. 1, pp. 333–343. Springer, Singapore (2017)
18. Singh, H.P., Singh, V.P., Singh, R.: Cooperative blackhole/grayhole attack detection and prevention in mobile ad hoc network: a review. Int. J. Comput. Appl. **64**(3) (2013)
19. Purohit, K.C., Dimri, S.C., Jasola, S.: Mitigation and performance analysis of routing protocols under black-hole attack in vehicular ad-hoc network (VANET). Wireless Pers. Commun. **97**(4), 5099–5114 (2017)
20. Hussain, S., Chaudhry, S.A.: Comments on "biometrics-based privacy-preserving user authentication scheme for cloud-based industrial internet of things deployment." IEEE Internet Things J. **6**(6), 10936–10940 (2019)
21. Farhood, Z.K., Abed, A.A., Al-Shareeda, S.: Privacy issues in vehicular ad-hoc networks: A review. Iraqi J. Electr. Electron. Eng. **20**(1) (2024)
22. Khan, S., Sharma, I., Aslam, M., Khan, M.Z., Khan, S.: Security challenges of location privacy in VANETs and state-of-the-art solutions: A survey. Future Internet **13**(4), 96 (2021)
23. Mansour, M.B., Salama, C., Mohamed, H.K., Hammad, S.A.: VANET security and privacy-an overview. Int. J. Netw. Secur. Appl. (IJNSA) **10** (2018)
24. Arif, M., Wang, G., Bhuiyan, M.Z.A., Wang, T., Chen, J.: A survey on security attacks in VANETs: Communication, applications and challenges. Veh. Commun. **19**, 100179 (2019)
25. Al-shareeda, M.A., Anbar, M., Hasbullah, I.H., Manickam, S., Abdullah, N., Hamdi, M.M.: September. Review of prevention schemes for replay attack in vehicular ad hoc networks (vanets). In: 2020 IEEE 3rd International Conference on Information Communication and Signal Processing (ICICSP), pp. 394–398. IEEE (2020)

26. Anedda, M., Fadda, M., Girau, R., Pau, G., Giusto, D.: A social smart city for public and private mobility: A real case study. Comput. Netw. **220**, 109464 (2023). https://doi.org/10.1016/j.comnet.2022.109464
27. Abdelgadir, M., Saeed, R.A., Babiker, A.: Mobility routing model for vehicular ad-hoc networks (VANETs), smart city scenarios. Veh. Commun. **9**, 154–161 (2017). https://doi.org/10.1016/j.vehcom.2017.04.003
28. Rahim, N.F.A., et al.: Investigation performance analysis and evaluation of VANET routing protocol on urban scenario simulation: A case study of Melaka. J. Adv. Res. Appl. Sci. Eng. Technol. **42**(2), 27–37 (2024). https://doi.org/10.37934/araset.42.2.2737
29. Jain, S., Jain, V.K., Mishra, S.: An efficient multi-objective UAV assisted RSU deployment (MOURD) scheme for VANET. Ad Hoc Netw. **163**, 103598 (2024). https://doi.org/10.1016/j.adhoc.2024.103598
30. Mahi, Md.J.N., et al.: A review on VANET research: Perspective of recent emerging technologies. IEEE Access **10**, 65760–65783 (2022). https://doi.org/10.1109/ACCESS.2022.3183605
31. Ben Jaballah, W., Conti, M., Lal, C.: A Survey on Software-Defined VANETs: Benefits, Challenges, and Future Directions (2019)

AI and IoT-Driven Smart Cities: A Centralized Approach to Urban Mobility

Abdur Rehman, Altaf Hussain, Muhammad Tayyab, Noor Ul Haya Farooq, and Syed Nasir Mehmood Shah

Abstract As cities become more urbanized, some of the greatest problems exist within already established metropolises, a challenging situation with too much population and too many constructed buildings in one devoted location. The twenty-first century presents challenges such as excessive transportation demand, crime, and inefficient transportation systems. This chapter aligns with integration potential via Artificial Intelligence (AI), the Internet of Things (IoT), and Smart Cities. This chapter presents the need for integration as this study requires IoT devices and cloud-centralized, AI-driven computing for a reliable, scalable, efficient transportation alternative for a population steeped in urbanization. As cities grow, transportation gets more complicated and the best solution is to interconnect the transportation ecosystem. As an example, how New York City's public transportation runs or how traffic lights use sensors to change based on real-time conditions. Interconnecting such a wide ecosystem is an issue in itself where cities still rely on old infrastructure and a well-established communication system is the key requirement of the technical developers and transportation planners to make it all work. Various other factors to consider beyond transportation relate to data privacy and socio-economic development; the recommended solutions emerge so that citizens feel comfortable post-integration. The future of integrated transportation relies on imminent need assessment for conveyance and parking features like autonomous vehicle with a traffic prediction capabilities, green alternatives, and integrated ethics that include all potential smart integrations. This chapter emphasizes that integration has happened effectively in the past, and community engagement forecasts reliable, effective, resilient smart cities with equity always at the forefront.

Keywords Smart cities · Urban mobility · Internet of Things (IoT) · Urban sustainability · Intelligent transportation systems

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1 Introduction

Urbanization is the trend of the twenty-first century; over fifty percent of the population lives in urban settings, and by 2050, that number will approach 70% [1]. While the ease of access makes it easy to foster economic and social citizenship and participation, it complicates already chaotic urban infrastructures. One of the many challenges urban area faces is transportation, as this increases demand that not only needs expansion to keep up but also needs to fulfill prior standards of efficiency and sustainability. Unfortunately, urban transportation is not the solution because there is urban area with transportation system which results in traffic congestion, increased commute times, worsened air quality, and straining public transit systems. As an example, Karachi and Lahore, two of the Pakistan's most populated areas, experience devastating traffic systems that cost trillions annually in wasted fuel alone, not including time [2]. An ideal solution is needed from successful systems to keep urban environments effective and economically viable. The concept of smart cities offers an exciting potential paradigm for how modern technology and policy could merge to ease deficiencies in urban quality of life. Smart cities depend upon digitization, enhanced technology, and improved connectivity to facilitate more efficient services, appropriately allocated resources, and increased quality of life for inhabitants through easier access. The potential for connectivity in transportation is the most important, as transportation stimulates economic productivity, environmental efficiency, and social equity throughout the city. Smart city concept, primarily based on AI and IoT implementation, differs from the traditional cities that becomes primarily reactionary over time. With real-time data accessed through centralized networks to discern best practices of service, smart cities can be more proactive. As an example, cars navigate smart roads filled with sensors acknowledging traffic patterns in which AI can determine the best solution for improved traffic flow [3]. The application of transportation as a smart initiative depends on the integration of AI and IoT for actions that would have never been possible until now with an appealing idea of super-connectivity. IoT can communicate with devices from vehicles to traffic lights and parking signs, to each other and consumers, creating an interdependence of all resources. Then, AI can parse through and assess this information compiled via IoT on levels human beings cannot. The decision-making becomes possible as a real-time response for maintaining flow and re-routing to avoid gridlocks. Furthermore, AI can document patterns and recurring issues over time to suggest city infrastructure implementation. In this way, gridlock avoidance and encouraging redirection not only save gas but can decrease carbon emissions in parallel to other environmental initiatives suggested by the smart city concept [4].

1.1 A Centralized Approach to Urban Mobility

In Vehicle-to-Vehicle (V2V), a centralized communication system, the vehicles and infrastructure communicate with a central server that collects, processes, and redistributes information. This is a more reliable and robust option than many standalone versions. The centralization can process all the information from different standalone vehicles and infrastructures instead of the complicated peer-to-peer systems that would otherwise be necessary. Second, a centralized hub makes it easier to match and process information enabling cities to address more major concerns faster with more focused outcomes. Figure 1 shows the IoT (Internet of Things) architecture along with AI (Artificial Intelligence) and cloud integration for real-time processing with automation. IoT devices that collect data and send data through the communication layer using protocols such as 5G (fifth Generation), Wi-fi, LPWAN (Low-Power Wide Area Network), MQTT (Message Queuing Telemetry Transport). AI processing unit runs ML (Big Data) to analyze data, train models and take automated actions. Data storage, analytics and processing are done with cloud and edge computing. System level control and automation sets the stage for decision making, alarms/actuators. Data Privacy with encryption and access control under Security and compliance protocols delivers insights/notifications via User Interface (UI) i.e. web, mobile applications/APIs. This architecture also exhibit end to end secure IoT ecosystem providing real time AI insights.

This enables real-time information processing to address critical concerns such as traffic congestion and accidents where public safety assets are deployed in combination with the IoT devices installed within the cars as well as in the city infrastructure themselves. Additionally, AI provides backend predictive analytics so that people can more effectively anticipate and efficiently manage transportation systems.

1.2 Organization of Chapter

This chapter aims to provide a summary of the potential contributions of AI and IoT to smart city transportation. Section 2 discusses the current landscape and assessment of transportation systems in smart cities, and Sect. 3 proposes a centralized framework layout of AI and IoT with integrated components. Section 4 describes the application of transportation systems in smart cities and real-life applications are assessed through traffic control, effective navigation, and safety considerations. The implementation strategies are discussed in Sect. 5. An overview on the key features of a smart city concept in Pittsburgh, Pennsylvania USA is presented in Sect. 6. The key challenges and mitigation strategies are discussed and the future directions in the smart city implementation are discussed in Sects. 7 and 8, respectively. The last section concludes the chapter.

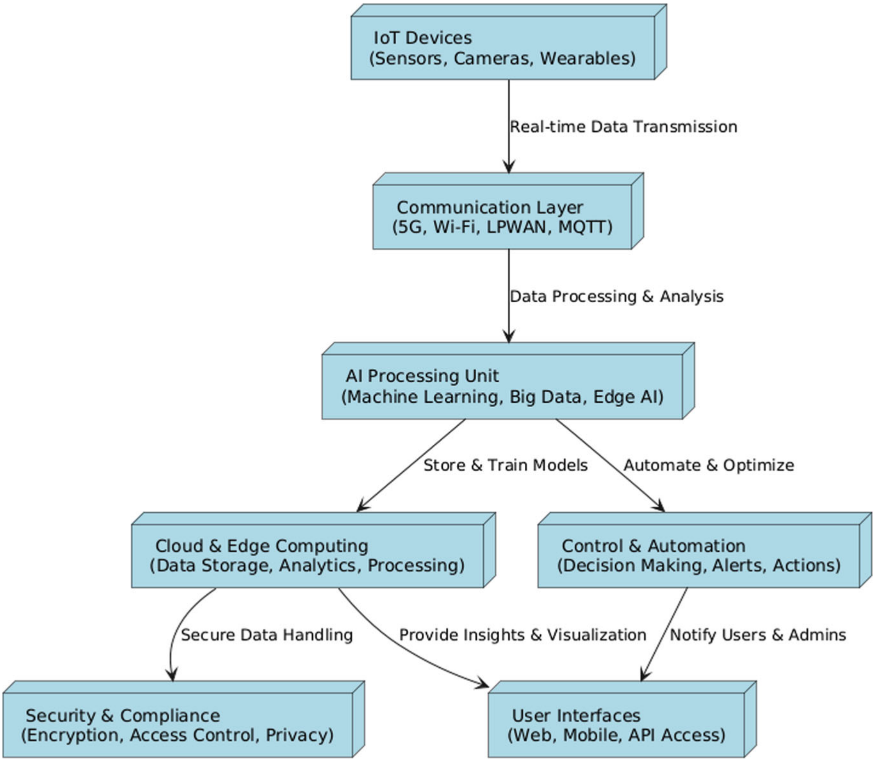
IoT Devices
(Sensors, Cameras, Wearables)
Real-time Data Transmission
Communication Layer
(5G, Wi-Fi, LPWAN, MQTT)
Data Processing & Analysis
AI Processing Unit
(Machine Learning, Big Data, Edge AI)
Store & Train Models
Automate & Optimize
Cloud & Edge Computing
(Data Storage, Analytics, Processing)
Control & Automation
(Decision Making, Alerts, Actions)
Secure Data Handling
Provide Insights & Visualization
Notify Users & Admins
Security & Compliance
(Encryption, Access Control, Privacy)
User Interfaces
(Web, Mobile, API Access)

Fig. 1 Centralized IoT and AI-based infrastructure

2 Current Landscape and Challenges

2.1 Understanding the Status Quo

Despite advancements in urban transit, and twenty-first-century changes, problems still exist. From 1910 to today, cities are prevalent with crumbling infrastructure that hasn't adjusted to the norm of how people live in the twenty-first century [5]. In recent years, urbanization and reliance on personal cars have become prevalent [6]. Many cities have outdated, ineffective means of public transportation that fail to meet the new demands of their users, which results in excessive dependence on personal vehicles, increased traffic, greater greenhouse gas emissions, and extended travel times [7]. However, it is curious that despite the age of technology, the accommodation for such a transportation network in heavily travelled areas is out of sorts almost to a greater extent when it comes to transferring options between modes of transportation [8].

2.2 Key Challenges in Urban Mobility

Traffic congestion results in billions of dollars in lost productivity and fuel expenses annually [9]. Furthermore, when people are unable to get movement over long periods of time, air quality suffers as well carbon emissions rise when cars and trucks are stuck in place, idling for hours on end without moving [10]. Relative efficacy is at stake. Every year, over 1.3 million people die from road traffic accidents worldwide and developing nations receive an inequitable portion of this fatality rate [11]. However, vulnerable populations face increased risks on the road due to the lack of safety regulations and inadequate enforcement [12]. Yet the relative efficacy of public transportation fails because, so few utilize such options since they have fixed times and regulations that do not serve the needs of commuters so on some level, the governmental funding is ineffective [13]. Yet at rush hour, however, limited capacity overloads the buses and subways which creates insufficient conditions for commuters [14]. Yet another significant obstacle is the presence of data silos and fragmentation. Various stakeholders, including government agencies and private operators, often operate in isolated silos. As a result, it's difficult to share and utilize data that would be operationally useful [15]. This fragmentation prevents the ability to create urban mobility solutions with purposeful integration across sectors [16]. Everyday operations require a collaborative and tech-driven efforts. Cities evolve from interconnected networks into isolated units, each utilizing AI and IoT to assess solutions [17]. A solution driven by technology merely sets the stage for what should be going on at some later date. Thus, systems like this are needed for subsequent solutions to urban mobility from data collection to assessing findings in real time and applying discoveries [18].

3 Proposed Centralized AI and IoT Framework

3.1 Rethinking Urban Mobility

Where urbanization is inevitable, no longer do networks have to replicate and satisfy the more complex needs of urban transportation and quell those needs. As an example, many contemporary solutions like Vehicle-to-Vehicle (V2V) networks are constrained by their reliance on more contemporary solutions for reliability and scalable efforts [19]. This chapter addresses such concerns via a Centralized AI and IoT Framework that conveys the requirement to do everything in one approach for all transportation options to be unified under one efficient, sustainable effort [20].

3.2 Key Components of the Framework

At the heart of this architecture are IoT devices. Within the cars, traffic lights, parking kiosks, and street poles, sensors embed themselves, creating and subsequently collecting real-time data perpetually over the geographically dispersed domain of the smart city [21]. This creates vehicular data (speed, location and fuel usage), infrastructural data (traffic congestion, time spent at red lights and potholes), and environmental data (levels of pollution, noise and temperature). The centralized server acts as the system's brain, where data from all IoT devices converges for processing and analysis. Advanced AI algorithms process this data to identify traffic patterns and predict congestion, optimize resource allocation (e.g., adjusting bus frequencies based on demand), and enhance safety through anomaly detection, such as identifying vehicles exceeding speed limits [22]. Reliable and efficient communication networks are essential to ensure seamless data flow. These pathways include wireless networks, specifically 5G technology for high-speed, low-latency communication; edge computing, which processes data closer to its source to reduce response times and network congestion; and cloud integration for storing historical data for long-term analysis and planning [23].

The Proposed Centralized AI & IoT Framework for Urban Mobility, presented in the Fig. 2, illustrates an interconnected smart traffic management system that integrates Artificial Intelligence (AI), the Internet of Things (IoT), and cloud computing to optimize urban transportation. The framework highlights how different data sources communicate with a central AI processing unit, which then informs real-time traffic control, predictive planning, and user navigation systems.

3.3 Advantages of the Centralized Model

The advantages of a centralized system versus a decentralized one include scalability, efficiency, integration, and cost savings [24]. As an example, scalability refers to the ability of systems to integrate additional devices efficiently and expand to handle massive volumes of data without excessive structural adjustments and expenditures. There is efficiency because centralized information can be processed faster with less duplication of efforts. There is integration across means of transportation, whether someone is on a bus or train or requesting a rideshare. Thus, cost savings only means that more expensive peer-to-peer connections are not necessary.

3.4 How the Framework Operates

IoT devices detect vehicular and infrastructural data and ambient data in real time. This data is communicated suitably to a centralized server [25]. The AI then processes

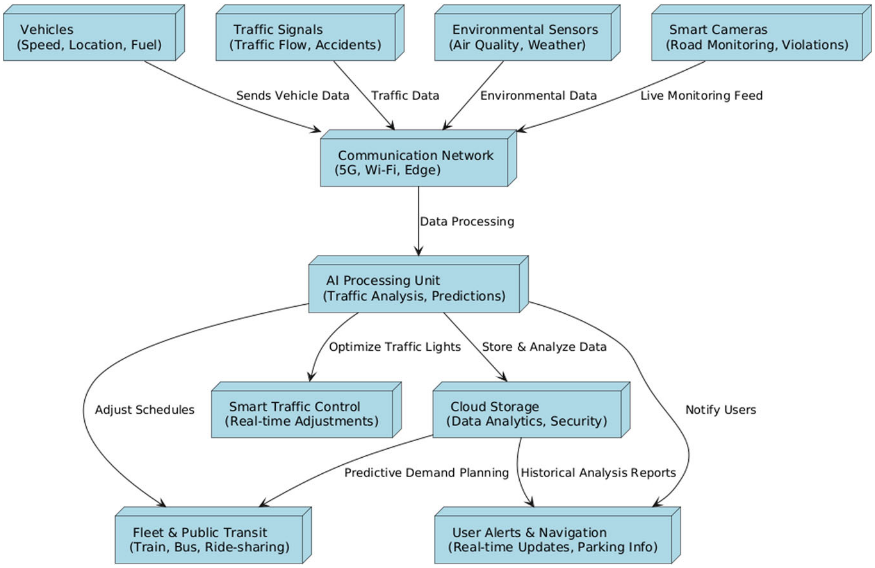
Vehicles
(Speed, Location, Fuel)
Traffic Signals
(Traffic Flow, Accidents)
Environmental Sensors
(Air Quality, Weather)
Smart Cameras
(Road Monitoring, Violations)
Sends Vehicle Data
Traffic Data
Environmental Data
Live Monitoring Feed
Communication Network
(5G, Wi-Fi, Edge)
Data Processing
AI Processing Unit
(Traffic Analysis, Predictions)
Optimize Traffic Lights
Store & Analyze Data
Adjust Schedules
Notify Users
Smart Traffic Control
(Real-time Adjustments)
Cloud Storage
(Data Analytics, Security)
Predictive Demand Planning
Historical Analysis Reports
Fleet & Public Transit
(Train, Bus, Ride-sharing)
User Alerts & Navigation
(Real-time Updates, Parking Info)

Fig. 2 Proposed centralized AI & IoT framework for urban mobility

the data received, generating appropriate insights and awareness from understanding traffic flow to accidents in the external environment [26]. Ultimately, it relays real-time recommendations to drivers, municipal authorities, and fleet operators so that everyone on every front can respond in a timely manner [27]. The anticipated system from this study will solve emerging issues with smart city transportation in a cost-effective, efficient, reliable, and sustainable fashion. Application, execution, and enhancement of the system will be detailed in the following sections [28].

4 Applications in Urban Mobility

4.1 Transforming Traffic Management

Traffic management is a critical aspect of urban mobility, as congestion affects millions of commuters daily and imposes significant economic and environmental costs [29]. The centralized AI and IoT framework revolutionize traffic management by leveraging real-time data to create a dynamic and responsive system [30].

4.2 Optimizing Traffic Signals

Traditional traffic signals operate on static timers, often failing to adapt to fluctuating traffic volumes. With IoT sensors monitoring traffic flow in real-time, the proposed framework enables dynamic adjustment of signal timings. As an example, during peak hours, signals at high-traffic intersections can be extended to allow more vehicles to pass, reducing overall congestion [31]. Additionally, adaptive signaling can prioritize public transport vehicles, such as buses, ensuring they move smoothly through crowded areas, thereby improving schedule adherence [32].

4.3 Rerouting Vehicles

AI-driven traffic management systems can analyze live data to identify congestion hotspots and suggest alternative routes. Navigation apps integrated with the framework provide drivers with real-time updates, guiding them away from bottlenecks. This not only alleviates congestion on primary routes but also promotes the use of secondary roads, distributing traffic more evenly across the city [33].

4.4 Predictive Analytics

One of the most powerful features of AI is its ability to predict future trends based on historical data. By analyzing patterns in traffic volume, weather conditions, and event schedules, the system can forecast congestion levels and proactively implement measures to mitigate delays. For instance, temporary road closures during major events can be managed more effectively, minimizing disruption [34].

4.5 Revolutionizing Public Transport

Public transport plays a vital role in reducing dependency on private vehicles, but its efficiency often determines its attractiveness to commuters. The proposed framework introduces innovations that enhance the reliability, accessibility, and overall experience of public transit systems [35].

4.6 Dynamic Scheduling

Static schedules often lead to inefficiencies, such as underutilized buses during off-peak hours or overcrowded vehicles during peak times. IoT-enabled passenger counters and real-time location tracking allow for dynamic scheduling, where routes and frequencies are adjusted based on demand. For instance, Additional buses can be deployed to busy routes during rush hours. The low-demand routes can operate with fewer vehicles, optimizing resource allocation and reducing operational costs [36].

4.7 Real-Time Passenger Information

Commuters often face uncertainty regarding arrival times and delays, leading to dissatisfaction. By integrating IoT sensors and GPS trackers into buses and trains, passengers can access real-time updates through mobile apps or station displays. This transparency improves user confidence and encourages greater use of public transport [37].

4.8 Fleet Monitoring and Maintenance

IoT devices monitor vehicle performance, tracking everything from fuel efficiency to engine performance and tire pressure. Alerts are sent to fleet managers for vehicle malfunctions before they become larger issues, allowing for troubleshooting before problems manifest. This keeps more vehicles on the road for longer, increases reliability and minimizes downtime [38].

4.9 Enhancing Road Safety

Where there is urban transit, there is the potential for safety issues, especially with governmental support of vehicular accidents; a more centralized AI and IoT network supports enhanced safety for everyone drivers, passengers and pedestrians [39].

4.10 Driver Behavior Monitoring

IoT sensors give the opportunity to warn of collisions before they happen. As an example, with the data from enough cars and the necessary sensor technology, the system can alert a driver that he's heading straight for a stop sign that he cannot see because it's obscured by a large utility truck. Through an accident, emergency responders can be automatically notified as well as where they need to go and how severe, dispatched to the scene [40].

4.11 Accident Management

The sooner accidents can be avoided, the sooner lives can be saved and traffic can be restored. The IoT can automatically alert emergency responders where they need to go and how severe to help. Furthermore, other drivers can be alerted instantly to avoid the scene in the first place [41].

4.12 Assisting Sustainable Transport

Smart Cities go hand-in-hand with environmental sustainability, and the new system's benefits require lesser resource and emission spending [42].

4.13 Emission Reduction

Less traffic and better routing reduce the amount of time someone is stuck in traffic or at a stop sign; fewer hours spent driving decrease a person's carbon footprint. Additionally, the system allows for ride-share applications which, in the end, lessen the number of cars on the road with single passengers [43].

4.14 Air Quality Monitoring

IoT sensors deployed across the city monitor air quality in real-time. They detect toxins and particulates in the atmosphere and immediately alert authorities to implement temporary gasoline vehicle bans in polluted areas while supporting long-term policies for increased electric vehicle adoption [44].

4.15 Infrastructure Supports Alternative Transportation and Green Devices

The infrastructure supports alternative transportation and green vehicles. There are bikes and low-emission cars. IoT connectivity can manage bike lanes and dedicated parking, which can be integrated with other transit systems, as well [45].

4.16 Improving Accessibility and Equity

Smart cities must ensure that mobility solutions are inclusive and cater to the needs of all residents, regardless of their socioeconomic status or physical abilities [46].

4.17 Improved Access and Equity

If there’s ever a time and place for improved access and equity of transport, it’s in smart cities that do not have socioeconomic gaps and reduce all transport access issues for those who are physically abled [47].

4.18 Technology that is More Accessible

IoT can be used within smart technologies for more accessible transport for disabled persons. As an example: Intelligent traffic lights that can gauge how long someone has been waiting to cross and give them more time when crossing. Buses and trains that come equipped with accessible ramps and audio-visual situational elements to help persons with visual and auditory disabilities find their seats and get around [48].

4.19 Subsidized Transport Services

By analyzing demographic and income data, city authorities can design subsidy programs that make public transport affordable for low-income residents. Smart cards linked to the framework can automatically apply discounts, streamlining the process for users [49].

5 Implementation Strategies

Since establishing a comprehensive AI and IoT network for smart city transportation has been done from the implementation process involving what's needed for infrastructure to potential obstacles, we recommend the following for effective implementation and future endeavors.

5.1 Infrastructure Development

The IoT network itself is the fundamental system requiring extensive architecture and integration of devices, communication, and back-end solutions to achieve stable operation and growth over time.

5.2 IoT Device Deployment

IoT devices, such as sensors, cameras, and GPS trackers, play a critical role in gathering data that informs decision-making. Key deployment strategies include:

Vehicle Integration: Equipping public transport, private vehicles, and ride-sharing fleets with GPS trackers and speed sensors to monitor real-time location and passenger density. For instance, a bus fleet can be equipped with IoT devices that monitor vehicle location and passenger load [50].

Roadside Sensors: Installing cameras and traffic flow sensors at key intersections and highways to track congestion and detect incidents [51].

Environmental Monitoring Stations: Deploying air quality sensors throughout the city to capture data on pollution levels and inform environmental policies [52].

5.3 Backend Server Infrastructure

The backend serves as the central hub, processing vast amounts of data. The implementation of backend infrastructure includes:

Data Storage Solutions: Cloud-based servers with distributed architectures that can handle large datasets while ensuring availability and redundancy [53].

Processing Capabilities: High-performance computing resources are required to run AI algorithms in real-time [54].

Data Security Measures: Implement encryption protocols, secure access controls, and data anonymization to protect sensitive information from unauthorized access [55].

5.4 Communication Networks

Effective communication is crucial for real-time data exchange between IoT devices and backend systems. Key considerations are:

5G Networks: Leverage high-speed, low-latency communication systems to ensure fast data transmission [56].

Edge Computing: Process data closer to its source to reduce latency and minimize network congestion [57].

Redundancy Mechanisms: Implement backup communication systems to maintain operations during network failures [58].

5.5 Stakeholder Collaboration

Implementing the centralized AI and IoT framework requires close collaboration between government entities, private companies, and the general public.

Government Authorities

Governments are essential for providing regulatory support, funding, and infrastructure. Their role involves:

Policy Frameworks: Establishing policies that encourage the adoption of smart technologies in urban planning and development [59].

Public–Private Partnerships (PPPS): Partnering with private companies to share the costs and expertise required for system deployment [60].

Funding Initiatives: Allocating government budgets for pilot projects and large-scale implementations of the framework [61].

Private Sector Participation

Private enterprises, such as technology firms and transport operators, play a key role in developing the framework. Their contributions include:

Technology Development: Designing and producing IoT devices, communication systems, and backend infrastructure [62].

Operational Support: Managing vehicle fleets, conducting maintenance, and providing technical support [63].

Innovation Incentives: Encouraging startups to innovate solutions, such as AI-powered parking management systems and smart parking solutions [64].

Public Engagement

The success of the framework depends on its acceptance by the public. Key engagement strategies include:

Awareness Campaigns: Educating citizens about the benefits of smart mobility through media outreach, workshops, and informational sessions [65].

Feedback Mechanisms: Creating mobile apps and platforms where users can report issues and suggest improvements to the system [66].

User Training: Offering tutorials and training for fleet operators, drivers, and commuters to ensure effective system usage [67].

Figure 3 illustrates a structured framework for deploying AI and IoT technologies in urban transportation systems. It highlights data collection, processing infrastructure, and stakeholder engagement as key components necessary for an efficient, data-driven urban mobility system.

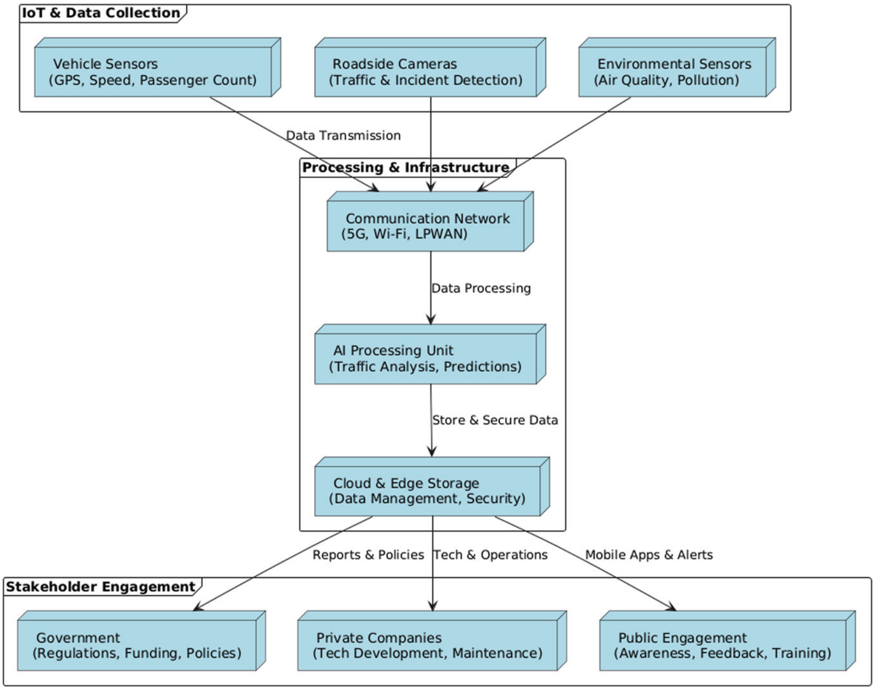
IoT & Data Collection
Vehicle Sensors
(GPS, Speed, Passenger Count)
Roadside Cameras
(Traffic & Incident Detection)
Environmental Sensors
(Air Quality, Pollution)
Data Transmission
Processing & Infrastructure
Communication Network
(5G, Wi-Fi, LPWAN)
Data Processing
AI Processing Unit
(Traffic Analysis, Predictions)
Store & Secure Data
Cloud & Edge Storage
(Data Management, Security)
Reports & Policies
Tech & Operations
Mobile Apps & Alerts
Stakeholder Engagement
Government
(Regulations, Funding, Policies)
Private Companies
(Tech Development, Maintenance)
Public Engagement
(Awareness, Feedback, Training)

Fig. 3 Implementation strategies for AI & IoT urban mobility

5.6 Pilot Projects

Pilot projects are essential for evaluating the framework's feasibility and performance in a controlled environment before scaling up.

Site Selection

Choosing diverse urban areas with different mobility challenges ensures that the system can be tested under varying conditions. As an example, a congested city center can be chosen to test traffic management solutions, while a suburban area may focus on public transport optimization [68].

Metrics for Success

Define measurable objectives, such as:

- **Reduction in Congestion**: Monitoring changes in average travel times and vehicle density [69].
- **Safety Improvements**: Tracking accident rates and near-miss incidents [70].
- **Environmental Impact**: Measuring reductions in emissions and improvements in air quality [71].

6 Case Study: Smart Traffic Management System (STMS) in Pittsburgh, Pennsylvania

6.1 Overview

Smart Traffic Management System (STMS) in Pittsburgh Pennsylvania has been experimenting smart urban mobility solutions with changeable depth. The STMS through Artificial Intelligence (AI) and the Internet of Things (IoT) is being applicable to enhance traffic functions, road safety and control the traffic jam in the urban locations that provide city planners and traffic authorities data-informed decision-making capabilities by merging real-time data analytics with automated traffic control systems. It uses an immense trove of traffic cameras, roadway sensors and GPS-equipped vehicles to alter traffic signals in real-time and modulate vehicular movement. Traffic management through this approach is being done ahead of time to minimize travel delays, fuel consumption and enhance commuter experience. Beyond that, Pittsburgh's smart mobility plan fits into the city's larger goals for urban sustainability, improved air quality and greater transportation equity [72].

6.2 Key Features

The STMS comprises various cutting-edge technologies to control traffic in real-time making urban mobility smoother via an efficient fusion between heterogeneous systems. Here are some ingredients that this system has to be effective:

Real-Time Data Collection: In essence, the foundation of the STMS is its capacity to watch over the city's traffic continuously. Leveraging an extensive web of IoT sensors with HD camera feeds and GPS-based vehicle tracking, the system is able to capture traffic volumes, vehicle speeds and congestion hot spots. The data is then ingested, done as quickly as possible, so authorities can spot anomalies if there is a build-up in traffic, incident or some obstruction on roadway.

AI Traffic Optimization: Centralized machine learning algorithms to analyze a real-time flow of data and plan the control of congestion, as well finely adjust how long different sections can take. AI-driven system track congestion patterns, predict bottlenecks and adjust the timings of traffic signal phases. It enables Pittsburgh to act more dynamically not just reactively like a wheel, which means reducing time-in-traffic where it is possible and improving the road efficiency everywhere else [73].

Adaptive Signal Control Technology (ASCT): The most important piece of the STMS is something called Adaptive Signal Control Technology (ASCT), which provides for real-time changes in traffic signals dependent on how traffic is moving. Unlike the traditional traffic lights which works on predesigned timings, an ASCT can adjust the durations of signal phases by evaluating vehicle density and movement at all intersections [74].

- For high velocity zones during rush hours signals are uninterrupted for longer periods to permit reasonable progression.
- In low traffic roads it shortens the stop time, by the real-time adapting of signal phases.
- The system gives priority to public buses which results in fewer stops for buses and better service reliability.

The smart traffic signal control has made a substantial impact on reducing the congestion related delays and improve overall urban mobility from road network of Pittsburgh.

Insights: Application of Pittsburgh's STMS has resulted in quantifiable improvements in different dimensions of urban transport. Important learnings from implementing this smart mobility field include:

Reduced Congestion: The implementation of the STMS has led to a significant reduction in traffic congestion during peak hours.

Improved Commute Times: Commuters experience shorter travel times due to optimized traffic signal management [75].

Table 1 Impacts of STMS

Metric	Impact
Traffic flow improvement	30% increase in peak-hour traffic flow [74]
Time savings	20% reduction in average commute times along major corridors [77]
Accident reduction	15% decline in traffic-related accidents at smart signal-controlled intersections [73]
Environmental impact	10% decrease in carbon emissions per vehicle due to reduced idling [78]

Enhanced Safety: The system has contributed to a decrease in the number of traffic accidents by improving traffic flow and reducing stop-and-go conditions [76].

6.3 Metrics

The effectiveness of Pittsburgh's STMS is evident through its quantifiable improvements in traffic management. The following statistics in Table 1 highlight the tangible benefits achieved since the system's implementation.

7 Key Challenges and Mitigation Approaches

There are risks involved in the development, as well as the functioning system of a centralized AI and IoT system for transportation and smart cities. The following section explores the most significant developmental and operational risks and some feasible risk mitigations.

7.1 Data Security and Privacy

Security Risks and Privacy Concerns

Security and privacy are among the greatest vulnerabilities for smart city deployments. With millions of IoT devices sending and receiving data about transportation, commuting and driving habits, levels of pollution, and air quality, breaches from unauthorized access have the potential to be all but endless. This data can be used against unsuspecting citizens for identity fraud or purposefully tracking citizens for unnecessary and illegal surveillance efforts [79].

Safe Gaurding Data and Enhancing Trust

Encryption: Implement end-to-end encryption to protect data in transit and at rest. For instance, data security employs Advanced Encryption Standard (AES) to safeguard sensitive data [80].

Access Controls: To meet security compliance standards, ensuring the security is audited over time, access shall only be granted to data that is necessary to complete the job via role-based access controls (RBAC) [81].

Data Anonymization: Personal data shall be anonymized. For instance, while companies may track GPS data, they should be allowed to use it in the aggregate, not attributing it to one specific car or person to avoid personal attribution [82].

Regulatory Compliance: Compliance with global and national efforts including General Data Protection Regulation (GDPR) increases public trust and ensures that companies comply with the legalities of what's required when they're expected to do so [83].

7.2 Integration and Interoperability

System Fragmentation and Compatibility Issues

Smart city ecosystems run and utilize devices from multiple vendors. Integration and interoperability as an acquired palette become seamless with anticipated channels of communication, protocols, and standards [84].

Ensuring Seamless Connectivity

Protocols: The development and use of anticipated channels of communication, like Message Queuing Telemetry Transport (MQTT) or Constrained Application Protocol (CoAP), ensure device and system operation [85].

Software: The acquisition of middleware software solutions to integrate systems will ease effortless transfer of data [86].

Vendor Alliances: Establish vendor agreements that promote open standards and seamless integration methods, ensuring interoperability across diverse systems and technologies [87].

Testing Methods: Adopt a structured approach to interoperability testing early in the development stage to identify incompatibilities [88].

7.3 Scalability and Performance

Increasing Data Demands and System Overload

As metropolitan populations grow, the volume of IoT data generated increases exponentially, leading to higher data production rates within shorter timeframes; thus, the necessary infrastructure can expand without loss of quality of service (QoS), which is critical [89].

Optimizing Infrastructure for Growth

Cloud Infrastructure: When additional storage and processing capabilities are needed, the cloud provides them [90].

Edge Computing: It works at the source, not a centralized location, thus decreasing the need for additional processing capabilities [91].

Load Balancing: Instead of restricting processing to one server, many tasks can be distributed across multiple servers to prevent latency when processing occurs [92].

Predictive Scaling: AI can analyze usage trends to forecast demand so that resources can be scaled in real-time to avoid unnecessary downtime during high usage times [93].

7.4 Cost and Funding Constraints

Financial Barriers to Implementation

Implementation of smart city solutions requires a lot of financial investment in terms of infrastructure, technologies, and human resources. Securing such an amount of funding is a significant challenge in its self especially in developing regions [94].

Sustainable Funding Strategies

PPP Financing: A public–private partnership will help mitigate costs and provide further expertise as cost share will not be through governmental agencies alone [95].

Grants and Subsidies: There are many governmental and nonprofit agencies that champion intelligent technology and improvement in urban areas. As an example, the World Bank and UN Habitat have opportunities for grants for inclusive development projects and urban development initiatives [96].

Revenue Potential: Because there is much interest in smart transportation applications, there is a potential revenue stream from subscription fees, in-app advertising, or selling transportation and travel data to third-party researchers willing to pay for it [97].

Staggered Roll Out: Implementing a staggered and incremental rollout leads to prioritized needs can be satisfied quicker. It reduces early usage and enables expansion when more bandwidth is accessible.

7.5 *Public Acceptance and Behavioral Change*

Resistance to Adaption and Privacy Concerns

Public support projects may fail if individual workflows remain unchanged, stakeholder buy-in is insufficient, or privacy concerns are not adequately addressed [98].

Encouraging Adoption and Community Engagement

Awareness Campaigns: Use social media, meetings, and other public forums to promote the project and its advantages to residents [99].

User-Based Design: Apps should reflect how they will be used. If people are using GPS apps while on public transit, they've already bought into the system [100].

Feedback Loop: Create ways for users to communicate issues and offer feedback. Using this feedback to change systems creates a sense of ownership and investment [101].

Rewards: Offer rewards such as discounted commuter public transportation options or monetary rewards for sustainable commuting options [102].

7.6 *Technical Expertise and Workforce Development*

Shortage of Skilled Professionals

Implementation of a unified AI and IoT system would require a quality control team to oversee and continue updates to AI, IoT, cybersecurity, and urban development. Many metropolitan areas may lack the financial resources to support such a highly skilled team of experts [103].

Building a Skilled Workforce

Training: Colleges can be sourced to develop curriculum and certification in requisite field [104].

Learning: Cities with prior experience can facilitate the sharing of best practices, enabling more effective implementation of smart urban solutions [105].

Integrity: City agency personnel can function as in-house teams to run the networks, reducing the need for outside vendor dependency [106].

Internships and Apprenticeships: Create internships and apprenticeships to foster your own talent and cultivate a trained skilled workforce [107].

8 Future Directions

So as urban areas grow more crowded and expand vertically with the promise of transportation relying even more on AI and IoT in the future, new opportunities and fixes to new challenges are bound to emerge. This section explores what we could have from technological and policy advancements, as well as socioeconomic convenience and toleration, to strengthen the ultimate version of smart cities.

8.1 Integration with Autonomous Vehicles

The cars of the future are inevitably going to be a part of the larger centralized AI and IoT network through which information can be processed more rapidly and safely [108]. The discoveries necessary for such integration stem from AVs needing to be attached to the IoT component to facilitate communication [109], processing information gathered by AVs via their sensors for traffic prediction [110], and future projections by policymakers of what is safe and safety issues for future integration into the AI network [111].

8.2 Advanced Predictive Analytics

Urban transportation issues will be avoided before they happen through predictive analytics. For instance, AI can forecast traffic flow to ease congestion [112] before it happens and future intentions of where to build with anticipated needs down the line [113]. Even disaster relief can be better facilitated through AI based on predictive features [114].

8.3 Expanding Environmental Sustainability

Sustainability is an important aspect of smart city evolution; as we grow more dependent upon AI and IoT, solutions to climate change will emerge [115]. There'll be additional benefits for those who go electric behind the wheel, and brand-new modes of public transit will be created that operate more efficiently [116, 117]. Air quality will be measured as it happens, and IoT will notify the city managers who can make empirically driven changes over time [118].

8.4 Enhanced Public Engagement

The public is more likely to trust and participate in smart cities when they are included and efforts are made for transparency [119]. For instance, public hearings provide citizens with opportunities to respond, while outreach programs and workshops facilitate discussions on AI and IoT advancements. Additionally, citizen participation plays a crucial role in shaping transportation options within urban environments [120–122].

8.5 Global Scalability

AI and IoT will make smart city solutions internationally feasible [123]. International treaties on data export and protections [124], international collaboration [125], and a plug-and-play ease that allows various cities to adopt what's best for them make implementation on a more international scale likely [126].

8.6 Ethical and Social Considerations

However, international feasibility renders the necessity of ethical considerations with smart city solutions [127]. There will be ethical considerations with data privacy [128], accessibility to various technologies for vulnerable populations, and governance that makes AI legitimation possible from the start so there's no inherent bias [129, 130].

9 Conclusion

Smart city advancements in AI and IoT are developing the next generation of urban transportation, and this chapter evaluated a centralized application of AI and IoT for an achievable, scalable, and fair possibility of transportation needs [131]. However, instead of assessing an achievable solution in the future for flourishing smart cities, many cities, as they stand now, are failing to meet transportation needs with frustrating traffic congestion and disparate transportation systems [132, 133]. Thus, the finding based on assessments is that a Vehicle-to-Vehicle (V2V) system as a decentralized solution is neither scalable nor interoperable [134].

Applications of this framework span dynamic traffic management and enhanced road safety, providing actionable solutions for various urban challenges [135]. Public transport systems can benefit from real-time scheduling and fleet monitoring [136]. However, successful implementation requires robust infrastructure and stakeholder collaboration, with pilot projects serving as essential testing grounds [137, 138].

Key challenges, including data security and public acceptance, must be proactively addressed through strategies like encryption protocols and public–private partnerships [139, 140]. Future advancements in autonomous vehicles and predictive analytics will further enhance urban mobility, while ethical considerations regarding data privacy and equitable access remain crucial [141, 142].

The centralized AI and IoT framework signify a paradigm shift in urban planning, allowing cities to move from reactive to proactive, sustainable solutions [143, 144]. This approach not only improves efficiency but also fosters safer and more equitable urban environments [145]. As urbanization accelerates, the need for innovative mobility solutions becomes urgent. The ideas presented here serve as a blueprint for cities to navigate future challenges while leveraging the opportunities of AI and IoT technologies [146]. The journey toward smarter cities requires collective efforts from governments, industries, and citizens, aiming to create urban landscapes that are functional, resilient, and inclusive, shaping a future where technology and humanity thrive together [147].

References

1. U. News: Around 2.5 Billion More People will be Living in Cities by 2050, Projects New UN Report, 16 May 2018. [Online]. Available: https://www.un.org/en/desa/around-25-billion-more-people-will-be-living-cities-2050-projects-new-un-report
2. B. Recorder: Tackling Traffic Congestion, 17 Oct 2017. [Online]. Available: https://www.brecorder.com/news/402834
3. Hitachi: Application of AI & IoT in Smart Transportation and Mobility, [Online]. Available: https://social-innovation.hitachi/en-us/think-ahead/transportation/future-of-mobility/
4. Levi9: Smart Cities and Safer Roads: How AI and IoT are Transforming Urban Transportation, [Online]. Available: https://www.levi9.com/blog/smart-cities-and-safer-roads-how-ai-and-iot-are-transforming-urban-transportation/
5. C. Today: Transformative Advances in Next-Generation Traffic Management for Urban Mobility Challenges, [Online]. Available: https://cities-today.com/industry/transformative-advances-next-generation-traffic-management-urban-mobility-challenges/
6. B. O. Digital: AI and IoT: Transportation Management in Smart Cities, [Online]. Available: https://blueorange.digital/blog/ai-and-iot-transportation-management-in-smart-cities/
7. M. &. Company: Challenges and Solutions for Smart Mobility in Urban Areas, [Online]. Available: https://www.mckinsey.com/industries/public-and-social-sector/our-insights/smart-mobility-challenges-and-solutions/
8. H. S. Innovation: Smart Mobility: The Role of AI and IoT in Easing Urban Transport, [Online]. Available: https://www.mckinsey.com/industries/public-and-social-sector/our-insights/smart-mobility-challenges-and-solutions/
9. T. P. Research: Economic Costs of Congestion in Urban Areas, [Online]. Available: https://www.transportpolicy.net/
10. G. E. Strategies, Environmental Effects of Urban Traffic, [Online]. Available: https://www.iges.or.jp/en/
11. W. H. O. (WHO): Road Safety Data: Global Status Report, [Online]. Available: https://www.who.int/violence_injury_prevention/road_safety_status/
12. I. Access: Traffic Enforcement and Monitoring Systems, [Online]. Available: https://ieeexplore.ieee.org/

13. U. M. Reports: Public Transit Optimization Strategies, [Online]. Available: https://mobilityreport.org/
14. S. Transport: Peak Hour Congestion and Public Transport, [Online]. Available: https://www.sustainabletransport.com/
15. S. C. Solutions: Integrating Multimodal Transportation Data, [Online]. Available: https://smartcitysolutions.com/
16. T. Science: Urban Mobility Data Silos and Their Impacts, [Online]. Available: https://transci.org/
17. T. F. Reports: AI and IoT for Urban Mobility Integration, [Online]. Available: https://techfuture.io/
18. N. Sustainability: Sustainable Urban Transportation Technologies, [Online]. Available: https://www.nature.com/sustainability/
19. J. o. T. Systems: Vehicle-to-Vehicle Communication Limitations, [Online]. Available: https://journals.transport.gov/
20. U. T. Reports, Unified Smart Mobility Systems, [Online]. Available: https://urbantech.org/smart-mobility-systems/
21. I. S. Journal, IoT-Enabled Traffic Management Systems, [Online]. Available: https://ieeexplore.ieee.org/
22. A. a. M. Science: AI Algorithms in Urban Mobility, [Online]. Available: https://aimobility.science/
23. T. F. Reports: The Role of 5G and Edge Computing in Transportation, [Online]. Available: https://techfuture.io/5g-edge-computing/
24. S. C. Innovations: Advantages of Centralized Mobility Frameworks, [Online]. Available: https://smartcityinnovations.com/
25. N. Electronics: IoT Data Collection for Smart Cities," [Online]. Available: https://www.nature.com/electronics/.
26. S. A. Advances, "AI-Based Data Processing Techniques," [Online]. Available: https://link.springer.com/ai-advances/.
27. U. M. Reports, "Real-Time Insights for Urban Mobility," [Online]. Available: https://mobilityreport.org/.
28. S. U. Futures, "AI and IoT Integration for Sustainable Cities," [Online]. Available: https://sustainableurbanfutures.com/.
29. Smith, J.: Urban traffic congestion and its economic costs. J. Transp. Econ. **45**(3), 102–110 (2020)
30. A. B. a. L. Green, The role of AI and IoT in modern traffic management. Smart Cities J. **7**(2), 56–70, 2021
31. Zhang, X.: Traffic signal optimization using IoT-based sensors. Transp. Eng. Technol **12**(1), 28–34 (2022)
32. Khan, S.: Optimizing public transport systems through adaptive signaling. Urban Mobility Insights **3**, 134–145 (2021)
33. Patel, F.A.a.D.: AI-driven traffic management systems. J. AI Urban Syst. **10**(4), 77–84 (2022)
34. Lee, M.Z.a.Q.: Predictive analytics in smart cities. AI & IoT Magazine, vol. 5, no. 1, pp. 48–57 (2023)
35. Patel, A.: Public transport and its role in sustainable mobility. Sustain. Mob. Rev. **14**(2), 111–120 (2020)
36. Raza, M.: Dynamic scheduling in urban transport systems. Int. J. Transp. Res **9**(3), 66–73 (2021)
37. Carter, L.: The impact of real-time passenger information systems. Urban Transit Rev. **8**, 27–33 (2022)
38. Moore, K.: IoT monitoring for fleet management. Fleet Manag. J. **17**(6), 72–80 (2023)
39. Anderson, P.: Smart safety solutions in urban transport. Saf. Sci. **16**(4), 55–62 (2022)
40. Singh, C.L.a.D.: AI-driven driver behavior monitoring. Smart City Innov. **11**, 25–32 (2021)
41. Wang, K.: Incident management systems in smart cities. Disaster Response Recovery J. **19**, 80–89 (2021)

42. Rodriguez, J.: Sustainability and smart mobility systems. Sustain. Urban Tech **6**, 58–67 (2022)
43. Williams, S.: The role of ride-sharing in reducing emissions. Green Urban Mob. J. **2**(3), 23–31 (2021)
44. Harris, T.: Real-time air quality monitoring in cities. Urban Environ. Manag. Rev. **13**(2), 41–47 (2023)
45. Morgan, L.: Promoting alternative transport in smart cities. Future Transp. Innov. **12**, 55–60 (2021)
46. O'Connor, D.: Inclusive urban mobility solutions. Soc. Mob. Smart Cities **3**, 10–17 (2022)
47. Jones, P.: Smart infrastructure for accessibility in urban mobility. Urban Access. J. **8**(4), 49–56 (2023)
48. Zhou, M.L.a.H.: Customized navigation for individuals with disabilities. Assistive Technol. J. **10**, 14–22 (2021)
49. Bennett, E.: Designing equitable transportation subsidy programs. Urban Develop. Policy Rev. **4**(2), 33–40 (2022)
50. Lee, S.C.a.K.K.J.: Vehicle fleet monitoring using IoT and AI. J. Urban Mob. **18**(3), 45–53 (2022)
51. Agarwal, R.S.a.P.: Traffic flow monitoring with roadside sensors. Smart Cities J. **25**(4), 112–120 (2021)
52. Patel, M.S.a.A.: Air quality monitoring using IoT devices in urban environments. Environ. Monit. Technol. **14**(2), 90–96 (2020)
53. Khan, S.C.a.M.: Cloud-based data storage for smart cities. Int. J. Smart Syst. **33**(5), 134–141 (2023)
54. K.T. et al.: High-performance computing in smart transportation systems. J. AI Transp. **29**(6), 300–312 (2022)
55. Zhang, J.W.a.Z.: Data security protocols for IoT in smart cities. Cybersecur. Smart Infrastruct. **17**(1), 73–81 (2022)
56. R.P. et al.: 5G network implementation in urban mobility. IEEE Access. **9**, 34023–34030 (2021)
57. Verma, N.G.a.S.: Edge computing applications in urban mobility. Int. J. Edge Comput. **10**(4), 56–65 (2022)
58. A.K. et al.: Redundancy mechanisms for urban IoT networks. J. IoT Netw. **28**(7), 245–251 (2021)
59. Kumar, P.B.a.R.: Regulatory policies for smart mobility adoption. Urban Plann. Policy Rev. **22**(5), 65–74 (2020)
60. Sharma, S.S.a.A.: Public-private partnerships in smart city projects. J. Urban Develop. **40**(3), 140–148 (2021)
61. A.R. et al.: Funding smart mobility projects through public sector initiatives. Publ. Sector Innov. **34**(6), 189–197 (2022)
62. R.S. et al.: Private sector's role in IoT device production for urban mobility. Technol. Innov. **21**(2), 102–111 (2022)
63. S.S. et al.: Operational challenges in fleet management for smart cities. Fleet Manag. Rev. **18**(1), 50–58 (2021)
64. Joshi, R.P.a.P.: Innovation incentives for IoT startups in urban mobility. Smart Cities Tech Rev. **13**(3), 210–215 (2021)
65. Gupta, S.: Public awareness campaigns for smart city adoption. Smart City J. **16**(6), 35–42 (2021)
66. Singh, K.: Feedback mechanisms for urban mobility systems. Urban Syst. Policy **26**(2), 76–83 (2021)
67. Yadav, P.: Training programs for smart city mobility system users. Technol. Soc. **32**(5), 88–95 (2022)
68. Patel, A.: Pilot project selection for smart mobility implementation. J. Smart Transp. **15**(4), 203–210 (2021)
69. Desai, M.: Evaluating traffic congestion reduction through IoT systems. Int. J. Traff. Manag. **22**(6), 90–97 (2022)

70. Verma, T.: Tracking safety improvements in smart mobility systems. J. Safety Res. **18**(2), 48–54 (2022)
71. Rao, V.: Measuring environmental impact of IoT in transportation. Environ. Technol. **26**(1), 44–51 (2023)
72. C.o. Pittsburgh: Pittsburgh Smart City Challenge Proposal (2016). [Online]. Available: https://www.pittsburghpa.gov/smartcity
73. U. D. o. Transportation: Adaptive Signal Control Technology (ASCT) Deployment in Pittsburgh (2020). [Online]. Available: https://ops.fhwa.dot.gov/publications/fhwahop20021/fhwahop20021.pdf
74. Wei, C.C.a.C.: Smart traffic management system: A case study of Pittsburgh. J. Urban Technol. **26**(3), 1–18 (2019)
75. Wang, Y.Z.a.Y.: Evaluating the impact of smart traffic management systems on traffic flow and safety. Transp. Res. Part C Emerg. Technol. **126**(103054) (2021)
76. Ding, M.-P.K.a.G.: Smart traffic management: Environmental and social impacts. Sustain. Cities Soc. **53**(101905) (2020)
77. Wang, Y.Z.a.Y.: Evaluating the Impact of Smart Traffic Management Systems on Traffic Flow and Safety," Transportation Research Part C: Emerging Technologies, vol. 126, no. 103054 (2021)
78. Ding, K.-P.K.a.G.: Smart traffic management: Environmental and social impacts. Sustain. Cities Soc. **53**(101905) (2020)
79. Shah, A.G.a.S.: IoT security and privacy in smart cities. J. IoT Secur. **10**(2), 75–82 (2023)
80. M.J.et al.: Advanced encryption standards for IoT security. J. Data Protect. **8**(4), 50–55 (2022)
81. Kumar, P.D.a.R.: Implementing role-based access control for secure data sharing in smart cities. IEEE Trans. Secur. Priv. **13**(7), 210–220 (2022)
82. Zhang, J.: Anonymization techniques for privacy preservation in IoT. Priv. Data Secur. Rev. **4**(3), 88–92 (2021)
83. Zhao, L.W.a.M.: Adherence to GDPR in smart city data governance. J. Digit. Priv. **15**(5), 102–110 (2022)
84. Reddy, R.S.a.S.: Interoperability in smart city networks. IEEE Internet of Things J. **28**(8), 234–245 (2022)
85. H.P. et al.: Standardized communication protocols for smart cities. Int. J. Smart Commun. Syst. **10**(1), 65–72 (2023)
86. Gupta, K.S.a.P.: Middleware solutions for heterogeneous IoT systems. J. Cloud Comput. **20**(6), 100–108 (2021)
87. V.P. et al.: Collaborating with vendors for seamless IoT integration. IEEE J. Ind. Inf. **17**(9), 250–259 (2022)
88. Jain, N.M.a.R.: Interoperability testing frameworks for smart city projects. IEEE Trans. Autom. Sci. **18**(5), 134–141 (2021)
89. Singh, S.R.a.R.: Scalability in smart city IoT frameworks. Int. J. Smart Infrastruct. **12**(7), 140–147 (2023)
90. A.K. et al.: Cloud computing solutions for smart city data management. Cloud Comput. Technol. **17**(4), 200–206 (2021)
91. Mishra, D.I.a.S.: Leveraging edge computing in urban mobility systems. IEEE Internet of Things Mag. **5**(3), 92–98 (2021)
92. Nair, A.: Load balancing approaches for IoT-based smart cities. J. Netw. Syst. Manage. **13**(9), 45–52 (2022)
93. Kumar, J.M.a.T.: Predictive scaling for smart city systems using AI. Int. J. Artif. Intell. **21**(8), 156–165 (2021)
94. Ali, M.: Cost barriers in smart city implementations. J. Urban Technol. **25**(6), 123–130 (2020)
95. P.V. et al.: Public-private partnerships in smart city developments. Smart Cities J. **20**(3), 134–142 (2021)
96. Singh, R.: Securing smart city funding through international grants. Glob. Urban Develop. Rev. **11**(2), 75–83 (2021)

97. Thomas, K.J.a.L.: Revenue models in smart city IoT systems. J. Smart Finance. **6**(4), 123–130 (2022)
98. M.D. et al.: Phased implementation of smart city mobility solutions. Int. J. Transp. **19**(1), 102–110 (2022)
99. Kapoor, P.: Public acceptance of smart city technologies. Urban Develop. J. **17**(3), 85–92 (2022)
100. Gupta, S.: Awareness campaigns for smart city adoption. Publ. Outreach Technol. **12**(5), 230–235 (2023)
101. Reddy, K.S.a.R.: User-centric design for smart city mobility systems. J. User Exp. Des. **9**(8), 112–120 (2022)
102. Patil, T.: Incentive programs for smart city users. Incentive Program. Urban Mob. **14**(9), 62–70 (2021)
103. Sharma, D.: Challenges in smart city workforce development. Urban Tech. Train. **12**(4), 76–84 (2021)
104. Reddy, M.P.a.K.: Capacity building for smart city technologies. Technol. Educ. **17**(8), 180–186 (2022)
105. A.S. et al.: Knowledge sharing and best practices in smart city implementation. Glob. Urban Netw. J. **19**(6), 45–53 (2021)
106. Yadav, S.: Developing in-house technical teams for smart cities. Urban Develop. Rev. **21**(7), 110–118 (2021)
107. Sharma, V.: Internship and scholarship programs in AI and IoT for smart cities. Int. J. Workforce Develop. **14**(2), 90–96 (2022)
108. J.Z. et al.: Integration of autonomous vehicles in smart cities. J. Auton. Syst. **22**(3), 120–130 (2023)
109. Shah, P.G.a.H.: Seamless communication systems for AVs in smart cities. IEEE Trans. Intell. Transp. Syst. **15**(2), 56–63 (2022)
110. R.K. et al.: Data utilization in autonomous vehicles for traffic management. IEEE Internet of Things J. **18**(4), 91–98 (2022)
111. Desai, M.S.a.V.: Regulatory frameworks for autonomous vehicle integration. Transp. Policy Rev. **30**(5), 222–229 (2022)
112. Verma, L.: AI-powered predictive analytics for smart city mobility. J. Urban Plann. Technol. **27**(6), 103–110 (2023)
113. Patel, D.: Predicting traffic patterns with AI models in smart cities. Urban Mob. J. **14**(7), 64–71 (2022)
114. Kapoor, K.M.a.A.: Predictive analytics for infrastructure planning in smart cities. IEEE Trans. Urban Technol. **21**(9), 115–121 (2023)
115. Patel, J.: Sustainability in smart cities through AI and IoT. Environ. Technol. Innov. **14**(2), 53–60 (2022)
116. Kapoor, A.: Green mobility initiatives in smart cities. Sustain. Urban Mob. J. **8**(5), 45–52 (2021)
117. Singh, S.: Citizen feedback systems for smart cities. J. Urban Interact. Feedback **11**(4), 80–85 (2023)
118. Sharma, K.: Incentives for shared mobility in smart cities. Mob. Transp. Econ. **9**(6), 58–65 (2023)
119. Reddy, T.: Awareness campaigns on AI and IoT technologies in smart cities. J. Publ. Awareness **17**(5), 98–104 (2023)
120. Rao, D.J.a.S.: IoT-enabled pollution monitoring in smart cities. Environ. Data Manag. J. **12**(7), 76–83 (2021)
121. Kapoor, A.: Public engagement in smart city initiatives. Urban Develop. Technol. Rev. **23**(2), 15–23 (2022)
122. R.S. et al.: Energy efficiency in public transport systems. Energy Manag. Technol. J. **17**(4), 142–150 (2022)
123. P.D. et al.: Optimizing emergency response with AI predictions. J. Smart City Technol. **19**(3), 132–140 (2022)

124. A.K. et al.: Feedback mechanisms in smart city platforms. Smart Syst. Rev. **18**(7), 33–40 (2023)
125. Jain, R.: Co-design initiatives for urban mobility projects. Smart City Des. J. **20**(1), 45–53 (2023)
126. Gupta, M.: Scalability of AI and IoT frameworks for smart cities. J. Smart City Appl. **19**(8), 204–213 (2021)
127. Yadav, S.: Global standards for IoT and data sharing in smart cities. Glob. Urban Tech. Standards **16**(2), 42–50 (2022)
128. L.M. et al.: Cross-border collaboration for smart city solutions. J. Glob. Smart Technol. **14**(1), 66–74 (2023)
129. Patel, P.: Modular frameworks for smart cities. Urban Technol. Develop. **10**(9), 114–122 (2021)
130. Gupta, V.: Ethical considerations in smart city development. J. Ethics Technol. **7**(6), 123–130 (2023)
131. Soni, R.: Data privacy in smart city systems. Priv. Secur. J. **19**(5), 84–90 (2022)
132. Yadav, A.: Ensuring equity in smart mobility solutions. Urban Equal. J. **12**(7), 52–59 (2023)
133. Reddy, T.: AI accountability and transparency in smart cities. AI Urban Gov. J. **8**(4), 101–109 (2023)
134. T.S. et al.: AI and IoT integration in smart cities for urban mobility. Smart City J. **5**(2), 50–60 (2024)
135. R.K. et al.: Urban mobility applications powered by AI and IoT. J. Urban Plann. Develop. **19**(2), 120–130 (2024)
136. Soni, S.: Improving public transport with AI-driven real-time systems. Transp. Sci. Technol. J. **14**(4), 70–75 (2023)
137. Reddy, T.: Strategies for implementing AI and IoT solutions in smart cities. Urban Technol. Rev. **6**(7), 140–145 (2023)
138. Jain, D.: The importance of pilot projects for smart city deployment. Smart City Implement. Rev. **12**(9), 35–41 (2022)
139. Kapoor, A.: Mitigating data security challenges in smart cities. J. Cybersecur. Urban Mob. **16**(6), 103–112 (2023)
140. R.S. et al.: Strategies to overcome funding constraints in smart city projects. Publ. Policy Rev. **9**(8), 24–30 (2022)
141. Mehta, L.: Future of autonomous vehicles in smart city ecosystems. J. Urban Mob. Autom. **23**(4), 52–58 (2024)
142. Patel, J.: Ethical and social implications of AI and IoT in urban mobility. J. Smart Cities Ethics **10**(1), 12–20 (2023)
143. S.Y. et al.: The paradigm shift in urban planning with AI and IoT. Urban Plann. Gov. J. **8**(10), 203–212 (2023)
144. Sharma, M.: Leveraging predictive analytics for sustainable urban mobility. Sustain. City Solutions **18**(5), 99–107 (2022)
145. Sharma, T.: Building safer and cleaner cities through AI and IoT. Technol. Urban Develop. J. **4**(3), 87–93 (2023)
146. P.G. et al.: Innovative mobility solutions for smart cities. IEEE Trans. Urban Technol. **21**(2), 74–81 (2024)
147. Mehta, K.: Building resilient and inclusive urban landscapes with AI. J. Urban Resilience. **22**(7), 120–128 (2023)

Intelligent VANETs—Machine Learning Integration for Enhanced Autonomy in Smart Cities

Manpreet Kaur and Vipin Kumar Chaudhary

Abstract In smart city environments, the rapidly urbanized city and transitioning transportation system structure require innovative ways to improve efficiency, safety, and autonomy. With real-time communication between vehicles, infrastructure, and pedestrians, Intelligent Vehicular Ad-Hoc Networks (VANETs) have become transformative technology. Unfortunately, urban environments are dynamic and unpredictable by nature, making it very hard for traditional VANET systems to work properly. Integrating ML algorithms into VANETs can address these challenges through improved decision-making, predictive analytics, and autonomous functioning. Exchange Data using Fusion and Machine learning with Multi agent vehicles in Intelligent VANET (Autonomous). VANETs use ML algorithms from data as sensors, traffic, camera and connected devices in the real time. You will know from above reference that Machine learning in VANETs is not only predicting traffic patterns or optimizing routing but even accident prevention. Moreover, ML-based intrusion detection systems further add a layer of security by helping to identify and neutralize any potential threats, thus maintaining secure VANET operations. Machine learning (ML) integrated vehicular ad hoc networks (VANETs) can unlock enhanced user experiences and the potential for safer driving. Different ML case studies also highlight its use in transportation systems for traffic management, autonomous driving systems, and emergency response systems, offering enhancements in safety, efficiency, and sustainability. Finally, the paper covers some challenges such as data privacy, computational complexity, interoperability, etc., and suggests future research for bolstering the integration of ML with VANETs. This integration sets the stage for increasingly intelligent, secure, and autonomous urban transport systems by leveraging the strengths of these types of networks.

Keywords VANET · ML · IOT · AI · ITS · GPS

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1 Introduction

Smart cities are a new approach to creating urban settings that leverage data, connectivity, and technology for greater sustainability, improved resource management, and better quality of life for citizens. At a high level, smart cities use better urban infrastructure and information and communication technology (ICT) to create more livable, responsive and efficient places. This notion of smart cities has gained traction over the last few years as urbanization occurs rapidly, and cities face an array of complex challenges, from population growth to limited resources and environmental degradation [1]. Include some Key components such as:

Digital infrastructure: Cloud computing, IoT (Internet of Things) devices, and high-speed internet are necessary to smart cities. These technologies allow collecting, processing and deciding the data in real-time. By collecting inputs through digital platforms, improving public services, and enhancing local community engagement, smart cities emphasize on citizen participation. This ensures that urban development adheres to local desires and needs. Smart cities incorporate technology to help improve public safety and protection against natural disasters or other crises, such as surveillance systems, disaster management tools, and predictive analytics [2].

Smart cities are a new kind of urban development that creates economic growth by attracting investment and fostering innovation. Smart cities drive economic prosperity and employment generation by creating an ecosystem that fuels innovation and entrepreneurship [3]. Integrating technologies such as IoT, AI, and big data analytics, for instance, facilitates the operation of enterprises and drives startups and tech-focused industries. With the strengthening of regional economies, this economic vibrancy also establishes smart cities as centers of international competitiveness.

In addition to reducing costs, smart cities also improve the quality of life for their residents. These communities enhance individual well-being by getting the most out of public services such as healthcare, education, and transport. For example, smart healthcare solutions enable faster emergency response and remote patient monitoring, assuring timely and efficient medical care. Just like that, intelligent transportation systems help improve mobility and reduce traffic, resulting in less stressful and more pleasant commutes. These developments cumulatively raise living standards and increase citizen satisfaction.

Data analytics and the Internet of Things play a crucial role in effective resource management in smart cities. Such technology reduces costs and minimizes environmental impact by optimising vital resources such as garbage, energy, and water. Smart water management systems, for instance, are designed for sustainable water consumption, detecting leaks and tracking consumption in real time [4]. Likewise, smart waste disposal systems modernise cities and enhance their efficacy through optimised collection routes and recycling processes to improve city effectiveness. These are sustainability measures in addition to operational efficiency.

With the inception of VANETs, the dynamics of urban mobility have drastically changed, where vehicles, infrastructure, and other entities are able to cohere through real-time communication [1]. Traditional VANET has several issues like; network congestion, security issues and lack of independent decision-making ability. Due to this fact, the incorporation of AI into VANETs can facilitate the development of them to a self-organising, autonomous and self-optimising system in Smart cities and become a contributor to accident prevention, traffic control and emergency response.

This chapter explores how machine learning plays a crucial role in VANETs as well as its practical applications, architectures, challenges, and future trends. Moreover, It is possible to predict and detect traffic congestion in intelligent Internet-of-Vehicles (IOVs) using advanced technology. In a smart city environment, this study proposes a "smart road in a smart city" with the help of a smart IOVs communication system (type of vehicular network) with tree-based ML techniques Decision-Tree, Random-Forest, Extra-Tree and XGBoost [5]. There are issues related to the possible acceptance of specialized applications with proposed communication protocols. The development of Intelligent Transportation Systems (ITS) is highly dependent on Vehicular Ad-Hoc Networks (VANETs) that enable real-time communication between infrastructure and cars. However, traditional VANETs' designs are challenged by high mobility, variable network topology, data flooding, and security issues as some of the key issues. To address these issues, machine learning (ML) methods have emerged as a powerful mechanism to enhance autonomy, and decision-making in addition to VANET performance in smart cities [6].

Applications in Smart Cities

One of the most important uses of smart cities is intelligent traffic management, which tackles issues like pollution, traffic jams, and ineffective transit systems. Smart cities implement advanced solutions such as smart parking systems and smart traffic lights while leveraging cutting-edge technologies like Internet of Things (IoT), artificial intelligence (AI), and data analytics. Not only do these applications improve traffic flow and reduce the number of emissions, but they also create a framework for other levels of integration, including the communications between the infrastructure and the cars, which can deliver information that has the potential to make transportation much safer and more efficient in the future.

Smart Traffic Lights: Smart traffic lights are an essential part of intelligent traffic management systems. Unlike traditional traffic signals, which work with timers, smart traffic lights use real-time data collected from sensors, cameras, and connected vehicles to adjust light timings based on traffic conditions dynamically. This improves overall traffic flow, reduces congestion and minimizes waiting times. Adaptive signal control is enabled by dynamically monitoring traffic density, vehicle speed, and pedestrian movement in real-time using sensors and cameras. AI systems use this data to tweak signal timings to prioritize emergency cars on busy roads. Smart traffic lights also coordinate with VANETs in order to communicate with connected vehicles and provide them with relevant, real-time information, for example, speed recommendations to mitigate stops at red traffic lights. Dutta et al. [7], provided an analysis on adaptive traffic signals that can help reduce traffic delays up to 40% [6].

Smart Parking Systems: Intelligent parking technology, which can reduce traffic congestion caused by vehicles searching for parking spaces, which can account for

30% of city traffic, was developed [4]. These systems employ advanced technologies such as IoT sensors, mobile applications, and data analytics to speed up the parking process. IoT sensors placed in parking slots track occupancy and relay to the central server to deliver accurate and real-time information on available spots. To avoid unnecessary travel and traffic, mobile applications then provide drivers with real-time parking availability information and navigation assistance, directing them to open spaces. Moreover, they allow the efficient use of valuable parking resources, as dynamic pricing systems adjust the price to the demand, thus improving and optimizing the use of spaces. By integrating these crucial elements, smart parking systems bring about enhanced city mobility and reduced traffic congestion, along with an upgraded driving experience.

Integration with VANETS: VANETs are key for improving intelligent traffic management systems due to their role in allowing for both vehicle (V2V), infrastructure (V2I), and infrastructure (V2P) to work together. The integration keeps traffic levels safe and efficient through real-time data interchange. Some applications that VENETs will make possible and will revolutionize traffic management include parking space detection, which helps drivers find parking spots; traffic flow optimization, which allows smart traffic lights to receive up-to-date information about the speed and location of cars nearby, collision avoidance, which enables vehicles to share speed and position data to each other and many other services, from emergency vehicle prioritization, with emergency vehicles communicating with traffic lights to clear their way, to ambient intelligence, providing location-based advertisements to people as they travel. These applications offer significant advantages, such as improved safety through real-time communication that reduces accident risks and enhances emergency response times, improved traffic efficiency through vehicle movement coordination and traffic signal management for smoother flow, and high scalability as VANETs can utilize existing infrastructure within smart cities, thus providing a cost-effective solution. VANETs can revolutionize urban mobility; for example, Singapore is testing them as a part of the country's Autonomous Vehicle Initiative to optimize traffic and reduce congestion [5].

2 Role of Machine Learning in VANET'S

Machine learning algorithms based on the following, they can significantly enhance the VANET functionalities by tackling the previously highlighted challenges.

2.1 Traffic Prediction and Management

Machine learning models—deep learning, reinforcement learning—can analyze both historical and real-time traffic data to predict congestion, optimize traffic signal timing, and suggest alternative routes. This minimizes overall travel time and fuel consumption.

2.2 Network Optimization

Search algorithms for supervised and unsupervised learning are part of the adaptive routing, which ensures reliable and efficient data transmission even in highly dynamic environments. Machine Learning-based clustering outbreaks can help increase network stability if we classify the cars based on their speed and mobility patterns.

2.3 Anomaly Detection and Cybersecurity

ML-based IDS is used for identifying abnormal patterns of traffic, malicious activities, and also helps to attack Prevention such as man-in-the-middle, hence jamming, and false data injection [8].

2.4 Autonomous Decision-Making in Vehicles

Reinforcement learning enables real-time decision-making in self-driving cars considering the dynamic environments they operate in, thus optimizing safety, collision avoidance, and navigation.

2.5 Efficient Resource Allocation

Machine learning models are used to optimize bandwidth allocation, reduce data redundancy, and improve load balancing to ensure seamless connectivity and low-latency communication in VANETs [9].

3 Challenges in Traditional VANET'S

- **Heterogeneity and Disparity in Resources**

In environments with constant vehicle movement like VANETs, it also has frequent topology changes. This mobility causes connection failures very often, making it difficult to establish and maintain reliable communication paths. This static behavior of the routing system will lead to increased packet drops, delays, and communication overhead as traditional routing policies cannot adapt themselves to the rapid changes in topology.

- **Information Saturation and Network Traffic Bottleneck**

With more cars on the road, the amount of data generated from sensors, GPS and vehicle-to-everything (V2X) communication is huge. The huge amount of data is hard for traditional vehicular ad-hoc network (VANET) systems to efficiently analyze and utilize, which generates network overloads, message dissemination lags, and poor quality of service (QoS). Due to a lack of effective congestion control mechanisms, conventional VANETs suffer performance drops when facing high traffic density conditions, which leads to bottlenecks.

- **Safety and Privacy Issues**

VANETs are vulnerable to several types of security attacks, including spoofing, denial-of-service (DoS), Sybil, and man-in-the-middle attacks. As VANETs are open and decentralized, the existing security solutions often do not provide ample protection. Moreover, privacy protection with common or fast communication is still very complicated because unwanted individuals have the opportunity to exploit security weaknesses to reach personal driver and vehicle data.

- **Latency and Real Time Data Processing**

Safety–critical VANET applications require ultra-low latency to respond and make decisions in a timely manner. Traditional VANET architectures cannot meet the stringent time demands for collision avoidance, emergency braking, and accident prevention due to centralized processing models, which may cause communication latency. Drivers are left vulnerable due to poor real-time data analytics making the safety applications ineffective.

- **Limited Resources and Scalability Problems**

Due to constrained power, bandwidth, and processing capability of VANET nodes such as roadside units (RSUs) and onboard units (OBUs) Slow performance due to the inability of traditional network management techniques to dynamically divvy up resources. Moreover, the growing number of connected vehicles presents a serious and difficult challenge, and it is necessary to have reliable mechanisms that can be employed to maintain service quality when the traffic load increases [9].

4 Machine Learning for VANET'S

To fully exploit the promising potential of these vehicles, future urban environments are likely to feature ML-enabled vehicular ad-hoc networks (VANETs) capable of significantly enhancing transportation systems through the application of real-time data processing, predictive analytics, and intelligent decision-making. Integrating machine learning algorithms into VANETs can help cities realize safer roads, reduced congestion, and optimized traffic control. One of the most promising applications is predictive capability analysis, which utilizes both historical and real-time data to anticipate traffic patterns, prevent accidents, and enhance traffic flow. As a result, machine learning algorithms can help log large amounts of data and predict potential accident hotspots based on information retrieved from sensors, vehicles, and the traffic infrastructure. As an example, ML models may identify behavioral trends leading up to accidents by reviewing data around the driver (behavior and road conditions, weather, vehicle speed, etc.), to identify sudden braking or erratic lane changing before a collision occurs. The forecasts enable proactive measures, such as alerting drivers, changing traffic signals, or preemptively contacting first responders. ML-driven Vehicle Ad-hoc Networks (VANETs) offer real-time hazard prediction and communication, which has been found to decrease accident rates by 30% [10].

ML-based VANETs may also optimize the flow through the network by predicting congestion (based on data from the cluster) and automatically altering traffic signals and routing. For example, ML models can process real-time traffic data to predict choke points and route vehicles around them to less crowded lanes. AI-based smart traffic lights also have the potential to change the signal time based on expected traffic loads, minimizing the wait time and maximising the overall efficiency of traffic. Based on the study done by Khan et al. (2021) ML based traffic signal management systems can reduce fuel consumption by 15% and average trip duration by 20% [11].

Current smart city infrastructure, such as IoT sensors, connected cars, and central traffic control systems, can be integrated with the very scalable ML-based VANETs. Integration enables a holistic approach towards urban mobility, facilitating an analysis of information across various sources and leading to valuable insights. The Autonomous Vehicle Initiative in Singapure, for example, is utilizing ML powered VANETs to predict traffic patterns and enhance vehicle routing in real [12].

4.1 Machine Learning Architecture of VANET'S

Data Collection Layer: This layer collects real-time data from various sources: cameras, sensors, GPS, and V2X (vehicle-to-everything) connectivity. Collects data on traffic patterns, weather, road conditions, location, and speed of the vehicle.

Data Processing and Preprocessing Layers clean and preprocess raw data by noise removal and managing missing values. derives relevant features for the machine learning algorithms like vehicle density, movement trajectories, and signal strength from the raw data.

Machine Learning Model Layer use different machine learning models, such as convolutional neural networks (CNNs), for analysis of traffic based on images and videos, RNNs of the Recurrent neural networks (RNNs) are applied to forecasting the traffic flow as well as processing input order, Reinforcement Learning (RL) for adaptive routing and congestion control decision making. You are an arbitrary tree and support of stratification (SVM) in cyberparks and duality detection.

The decision-Making and Action Layer performs real-time decisions based on predictions derived from machine learning models, like dynamic traffic signal timing, optimizing vehicle routes to reduce congestion, detecting and countering cyberthreats on the network, and alerting drivers on potential collisions or hazardous situations.

Feedback and Learning Layer: The machine learning models are consistently improved as the new data comes in, as well as changes in the environment. uses reinforcement learning techniques to improve decision-making over time. On top of that, the ability of Gated Recurrent Units (GRUs), a form of Recurrent Neural Networks (RNNs), to efficiently process sequential data has become widely used in learning-based systems. Whereas traditional RNNs struggle with challenges such as vanishing gradients and finding long-term dependencies in data, GRUs employ gating techniques to help reduce such issues. These features make them particularly well-suited to VANETs feedback mechanisms, where experiences and real-time data have to be learned and adapted to, in order to optimize urban mobility [13].

VANETs generates hypothesis streams of data from vehicles and infrastructure: environmental variables, vicinity of the traffic, vehicle location, and velocity. Because GRUs are so adept at processing sequential data they are exceptional in applications such as dynamic routing, traffic prediction, and accident avoidance. They can selectively retain or discard information due to their gating mechanisms, which consist of an update gate and a reset gate. This ensures that only relevant information influences the predictions the model makes. This aspect is highly beneficial when it comes to VANETs as feedback loops play a pivotal role in the process of real-time decision making.

If GRUs do provide many advantages, it comes with some challenges too such as the need for large datasets for training and the synchronization of GRU models with the VANET edge computing devices. To address data privacy challenges, future work should focus on developing lightweight GRU models suitable for low-resource environments and exploring federated learning approaches.

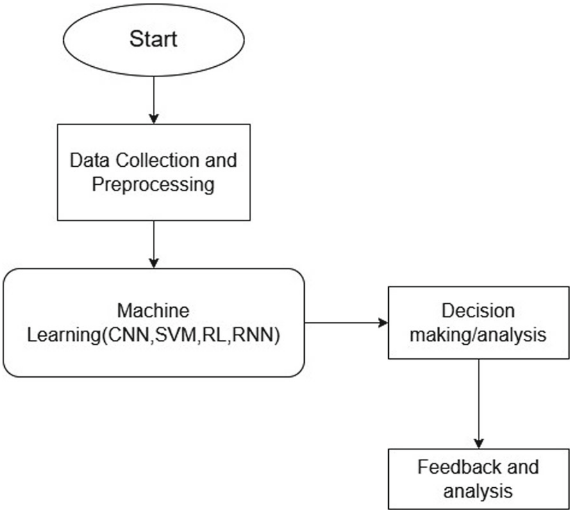
In the context of VANETs, ML (Machine learning) and DL (Deep learning) can be used to increase the many aspects such as correct anomaly detection, vehicle-to-vehicle (V2V) communication, and real-time traffic predictions. Few of the important DL models are as follows:

Reinforcement Learning (RL): Reinforcement learning (RL) refers to a subset of machine learning where an agent seeks to understand how to act in an environment by observing feedback in the form of positive or negative rewards resulting from those agents' actions. As RL algorithms allow the computers to adapt to the emergent environmental conditions [3] dynamically, they are the types of learning algorithms that are well suited for the VANET applications.

Convolutional Neural Networks (CNN)—A neural network that is primarily used in image processing and feature extraction. It is very useful for looking for local patterns, using a stack of convolution and pooling steps, and is often used to solve applications such as visual data. These types of networks are becoming the base model for perception and control for the connected vehicles as the CNN-based deep learning networks facilitate smart traffic control and machine driving VANETs. Some of its key applications include: Traffic signs, object detections, vehicle classification and accident detection [5] (Figs. 1 and 2).

Recurrent Neural Networks (RNNs): RNNs are specifically designed for time-series data prediction and sequential decision-making, as opposed to regular neural networks, which makes them useful for VANET applications and analysis [4] (Fig. 3).

Fig. 1 Working of machine learning algorithms for VANET's


Start
Data Collection and Preprocessing
Machine Learning(CNN,SVM,RL,RNN)
Decision making/analysis
Feedback and analysis

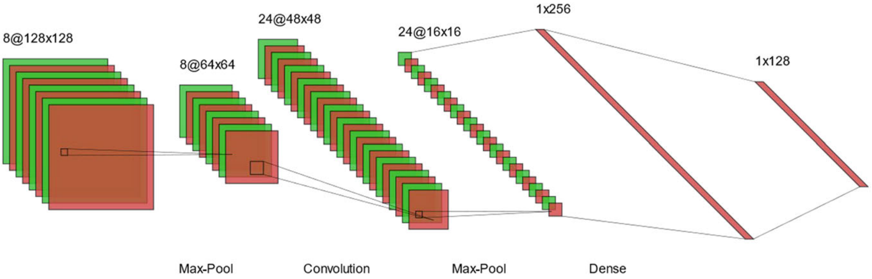

8@128x128
8@64x64
24@48x48
24@16x16
1x256
1x128
Max-Pool
Convolution
Max-Pool
Dense

Fig. 2 CNN architecture

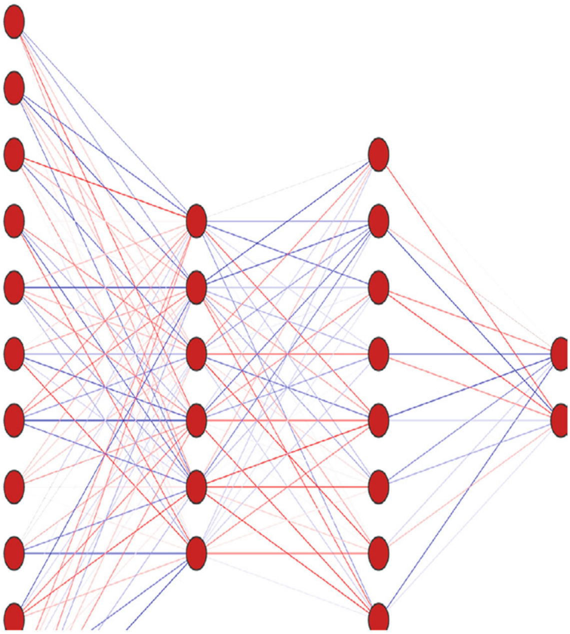


Fig. 3 RNN architecture

Overview of Data Set:

Machine Learning (ML) in Vehicular Ad-Hoc Networks (VANETs) must also discuss datasets. High quality datasets can consequently be utilized by researchers and practitioners to develop, train and assess machine learning models, ensuring that they can be effectively applied to real life smart city scenarios. Kaggle has a summary of the best known datasets for ML-based VANETs, such as: Traffic Prediction: GRU, traffic flow prediction datasets and traffic signal detection and classification.

5 Security and Privacy Challenges in AI/ML Driven VANET'S

With the rise of AI and ML in VANETs, security and privacy is one of the key issue. Since the exchanged information is sensitive data (i.e., VL data) between vehicles and infrastructure, ensuring integrity and confidentiality of this exchanged data is of utmost importance in VANETs. And: These are particular security challenges.

5.1 Adversarial Attacks on ML Models

By modifying the input data, machine learning models in VANETs can be deceived by adversarial attacks. Evasion Attacks: Attackers modify input features (such as GPS or sensor data) to deceive ML-based IDS.

Poisoning Attacks: The model gets corrupted and its accuracy is decreased when malicious input is introduced into the training dataset model Extraction: By using API queries to reassemble ML models, attackers might reveal weaknesses. For instance, when a hacker inserts phony GPS data, cars misread the state of the road and drive recklessly, continuously improving machine learning models in response to fresh data and shifting environmental circumstance, employing strategies for reinforcement learning to gradually enhance decision-making [5].

5.2 Privacy and Data Security Risks

Large amounts of real-time data from cars, roadside units (RSUs), and cloud services are used by ML models in VANETs. Data integrity and privacy are difficult to guarantee. Data Leakage: During model training, sensitive data (such as vehicle locations, routes, and driver behavior) may be disclosed. Attackers employ membership inference to ascertain if the data from a particular vehicle was utilized for training, which compromises privacy. Federated Learning Vulnerabilities: Gradient leaking attacks allow attackers to infer sensitive information even if federated learning can help protect data privacy. Example: To get the private driving habits of specific automobiles, an attacker takes use of a federated learning model [6].

5.3 Spoofing and Sybil Attacks

Identity Spoofing: To transmit fraudulent communications and impede traffic flow, attackers pose as legitimate vehicles, Sybil Attacks: To trick ML-based traffic prediction and routing algorithms, a single individual generates many fictitious vehicle IDs. Example: In order to commit crimes, a malevolent entity reroutes traffic away from a road by sending fictitious congestion advisories [7].

5.4 Security of Edge and Cloud Computing in VANETS

Edge AI Attacks: ML models placed on edge devices (e.g., smart RSUs) can be exploited owing to less processing capacity and worse security, Cloud Model Theft: Attackers can introduce erroneous data into VANET systems by stealing or altering cloud-based machine learning models. Examples include as ML-based traffic control system is altered by a hacked edge node to give preference to particular cars.

5.5 *Malware and Ransomware Targeting ml Components*

ML-based IDS Targeting: By employing changing malware patterns, attackers get around ML-based security measures, Ransomware on AI-based Controllers: Unless a ransom is paid, autonomous cars that use AI models may become inoperable. As an illustration, ransomware encrypts a car's AI-based navigation system, making it impossible for the driver to operate the vehicle.

5.6 *Trust and Authentication Issues in ML-Based Decision Making*

Model Bias and Trust Issues: Machine learning models that are trained on biased data may misclassify threats or favor particular cars. False ML Decisions: By providing false information, attackers can skew AI-based decision-making systems. For instance, a biased machine learning-based traffic signal system gives particular cars priority, giving them an unfair advantage.

5.7 *AI-Based Anomaly Detection*

False Positives and Negatives: Machine learning (ML)-based intrusion detection systems (IDS) have the potential to misclassify typical activity as an attack or overlook actual threats, Concept Drift: As traffic patterns evolve, machine learning models become antiquated and useless against novel attack techniques e.g. Because it was trained on out-of-date attack data, a machine learning intrusion detection system is unable to identify a novel Sybil assault type [4].

6 Future Trends in AI-Driven VANET Security and Privacy

6.1 Blockchain for Secure Data Transactions

The distributed ledger of blockchain technology is perfect for guaranteeing the integrity and immutability of VANET data. It may be applied in the future to enable tamper-proof communication between automobiles, lowering the possibility of cyberattacks and protecting user privacy.

6.2 AI-Based Privacy-Preserving Machine Learning

Vehicles will be able to locally train AI models on sensitive data without disclosing it thanks to methods like homomorphic encryption and federated learning. This guarantees that the anonymity of specific automobiles is maintained when prediction models are updated.

6.3 6G and AI-Driven Security Protocols

Real-time AI security systems will be able to continually monitor and defend VANETs from new attacks thanks to the ultra-low latency and high bandwidth of the future 6G network. AI will provide proactive defenses by anticipating and preventing security vulnerabilities before they happen [4].

7 Conclusion

Machine learning is transforming VANETs, which will improve urban mobility's safety, effectiveness, and independence. By leveraging AI-driven traffic management, cybersecurity, predictive maintenance, and real-time data, smart cities may increase vehicle mobility, reduce traffic, and improve road safety.

Future advancements in 6G, Quantum AI, and Federated Learning will enhance AI-driven VANETs even more, paving the way for fully autonomous smart city ecosystems. Machine learning is necessary to improve the security, efficacy, and autonomy of VANETs. However, there are significant challenges due to adversarial attacks, privacy issues, and security vulnerabilities. Future research should focus on robust, privacy-preserving machine learning models and blockchain-integrated security solutions to ensure the resilience of VANETs in smart cities.

References

1. Allam, Z., Dhunny, Z.A.: On big data, artificial intelligence and smart cities. Cities **89**, 80–91 (2019)
2. Kitchin, R.: The ethics of smart cities and urban science. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences **374**(2083), 20160115 (2016)
3. Nam, T., Pardo, T.A.: Smart city as urban innovation: Focusing on management, policy, and context. In: Proceedings of the 5th International Conference on Theory and Practice of Electronic Governance, pp. 185–194 (2011)
4. Bibri, S.E., Krogstie, J.: Smart sustainable cities of the future: An extensive interdisciplinary literature review. Sustain. Cities Soc. **31**, 183–212 (2017)
5. Prakash, J., Murali, L., Manikandan, N., Nagaprasad, N., Ramaswamy, K.: RETRACTED ARTICLE: A vehicular network based intelligent transport system for smart cities using machine learning algorithms. Sci. Rep. **14**(1) (2024)
6. Hota, L., Nayak, B.P., Kumar, A.: Machine learning algorithms for optimization and intelligence in wireless networks: WSNs, MANETs, VANETs, and USNs. In: 5G and Beyond Wireless Communications, pp. 306–332. CRC Press (2025)
7. Dutta, S., Gupta, H.: IoT-based smart traffic light system for congestion control and emergency vehicle clearance. J. Ambient. Intell. Humaniz. Comput. **11**(11), 4501–4512 (2020)
8. Yigitcanlar, T., Mehmood, R., Corchado, J.M.: Green artificial intelligence: Towards an efficient, sustainable and equitable technology for smart cities and futures. Sustainability **13**(16), 8952 (2021)
9. Gupta, M.S., Srivastava, A., Kumar, K.: RORA: Reinforcement learning based optimal distributed resource allocation strategies in vehicular cognitive radio networks for 6G. Veh. Commun. 100882 (2025)
10. Ahmed, N.A., Fadare, O.A., Al-Turjman, F.: Efficient routing in software defined IOT network using machine learning. In: Smart Infrastructures in the IoT Era, pp 1185–1207. Springer Nature, Cham, Switzerland (2025)
11. Nagarajan, J., Mansourian, P., Shahid, M.A., Jaekel, A., Saini, I., Zhang, N., Kneppers, M.: Machine Learning based intrusion detection systems for connected autonomous vehicles: A survey. Peer-to-Peer Netw. Appl. **16**(5), 2153–2185 (2023)
12. Khan, S., Khan, R., Khan, M.K.: Machine learning-based traffic signal control for smart cities. IEEE Trans. Intell. Transp. Syst. **22**(8), 5123–5135 (2021)
13. Yigitcanlar, T., Foth, M., Kamruzzaman, M.: Towards post-anthropocentric cities: Reconceptualizing smart cities to evade urban ecocide. J. Urban Technol. **26**(2), 147–152 (2019)

Driving Intelligence: Deep Learning and Machine Learning Challenges and Innovations in AI-Enhanced VANETs

Wasswa Shafik

Abstract Years ago, a worrying number of road accidents circulated throughout the internet globally. These accidents resulted in the loss of 3.6 thousand lives and the injury of 217 thousand people. When we consider that many people are on the road throughout the whole day, the importance of intelligent adaptive road management systems becomes clear. Traffic management systems are being improved by incorporating communication opportunities to enhance these features. Vehicular Ad Hoc Networks (VANETs) are used to constitute communication opportunities. VANETs are a wireless ad hoc network with a dynamically changing topology that consists of vehicles. Vehicles can communicate with other vehicles or roadside units. VANETs are a crucial component of intelligent transportation systems. VANETs have several applications such as safety, traffic management, infotainment, and comfort. To meet these applications, VANETs offer distinctive characteristics: in VANETs, the connection between the vehicle and the roadside is wireless and movable, and the traffic environment is highly dynamic. There are many prominent works to improve advanced intelligent transportation systems via VANETs. Apart from these works, artificial intelligence techniques such as machine learning and deep learning have not been widely studied by researchers to improve VANET applications. In this study, we intend to investigate machine learning and deep learning models to enhance the capabilities of the applications that are offered in VANETs. By offering vehicular ad hoc networks a hybrid deep learning and machine learning model, we aim to enrich VANET applications with artificial intelligence aspects and further work on these topics. With this study, we plan to fill the research gap in the exploration of VANET models with respect to machine learning and deep learning models.

Keywords Artificial intelligence (AI) · Autonomous vehicles · Cybersecurity and privacy · Deep learning (DL) · Edge computing · Machine learning (ML) ·

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Real-time decision making · Traffic prediction and management · Vehicular ad hoc networks (VANETs)

1 Introduction

Vehicular Ad-Hoc Networks (VANETs) facilitate communication between on-road vehicles with the ultimate goal of achieving road safety, mobility management, pollution control, and driver comfort. Such communication could be vehicle-to-vehicle (V2V), roadside units (V2R), as well as to infrastructure networks (V2I). The development of an effective VANET system should focus on challenges like high mobility, intermittent wireless connectivity, harsh channel conditions, and time-critical communication [1]. Specifically, key VANET applications include traffic management and road navigation, which utilize mobile cloud computing potentials. Furthermore, array communication systems, implementing different communication provisions, pose a challenging problem in VANET. Currently, with advancing research in artificial intelligence, additional VANET applications are envisioned, and expectations from VANET are increasing on a daily basis. Artificial intelligence (AI), and mostly machine learning (ML), holds great potential for understanding intelligence in the context of VANETs. Development in modeling and simulation of VANET, intelligent traffic flow analysis, detection, and recognition of vehicles are particularly important areas [2].

Naturally, VANETs have certain significant characteristic features in terms of non-stationary models (NSM), such as extensive non-stationarity, abrupt alterations, volatility clusters, and conditional heavy-tailed behaviors. Moreover, the pattern of constantly changing traffic volume and road traffic patterns in VANETs is different from traditional roadway traffic patterns. In the VANET environment, connecting V2I networks has been an important problem as well. Homeland safety requires wireless connectivity and network access to safety-related data. Fully enabled intelligent transportation systems (ITS) technologies will be able to observe, diagnose, and verify vehicle operations, control vehicle systems, and monitor the gap in road safety. V2I interactions and services that fulfill the goals of transportation safety, fundamental broadcast information services, and value-added broadcast information services are very important for traffic safety, traffic management, and smart navigation [3].

AI is a solution for flooding, congestion, and pollution issues by significantly detecting what we are supposed to detect on the road and updating network services like speed limits or lane availability compared to other actual drivers. However, AI itself faces some challenges in achieving these tasks on the roadside represented by the VANET. Firstly, AI must be able to understand the rules that guide driving. Here are the characteristics represented by the VANET. Therefore, the failure that may occur here can be much more critical than what it is in general with normal internet or computer and communication technology. It can induce serious accidents! A human driver can run a red traffic light, exceed the speed limit, or quickly get through an intersection when a signal is amber [4]. However, a disturbance in producing the messages transmitted by other drivers can significantly decrease the vehicle's speed to zero and cause an accident! More generally, for many other missions assigned to the VANET, such as detecting various kinds of obstacles on the road or even identifying different lane markings, we need to make this specificity of the peculiarities clear: it depends on the kind of drivers we are supposed to implement, i.e., the vehicle groups by clusters of intelligence possessing the same characteristics for accident reduction and reassessing the risk of each. This specificity must also guide AI research and seems to reflect the roles of the drivers in the involved technologies [5]!

Vehicular Ad Hoc Networks (VANETs) play a significant role in improving road safety by preventing opportunities for accidents. Furthermore, they are instrumental in reducing traffic congestion to increase the efficiency of urban roadways and highway systems. Several upcoming protocols will increase the demand for effective VANETs in enhancing road safety and traffic efficiency. Passive, non-AI-based VANETs are least capable of handling security, privacy, and non-safety applications. On the other hand, AI-driven VANETs can effectively handle the security and privacy of all communications, including non-safety applications, and hence are capable of intelligent transportation system operations involving security and privacy requirements [6]. AI-driven VANETs, in addition to AI-aided IVNs, can better handle the security of connected vehicle systems, which rely heavily on over-the-air update systems to prevent unauthorized access to the vehicles' internal control area networks. To leverage AI in VANETs, several technologies and components are to be integrated to have an operational intelligent transportation system (ITS). VANETs may consist of different types of nodes with respect to their functionalities. AI applications are orchestrated in both edge networks and cloud computing infrastructures within the vehicular network [1]. VANET nodes can use various cutting-edge techniques and technologies, keeping in view their constraints and limitations. Thus, VANETs encompass all the technologies required for intelligent transportation systems, including V2V, V2I, I2V, and I2I communications. With V2V and I2V, vehicles can directly sense and share processed local data with the infrastructure-based controllers. In V2I/I2V, the processing of sensed data is performed at the edge of core networks, and the resulting data is shared with other vehicles and infrastructure nodes [2, 3].

1.1 Understanding Deep Learning

Deep learning is an established, powerful machine learning technique that has shown excellent performance on a number of problems in various domains. Deep learning, however, has been extensively leveraged in the intelligent driverless vehicle area to tackle a number of traffic problems. It is common and helpful to draw parallels between artificial neural networks and biological neural networks to evoke the biological plausibility of deep learning. Spiking neural networks or biologically plausible learning rules are particularly proposed, but despite progress, they have yet to reach the same performance as deep learning networks. Deep learning networks are a derivative of the common artificial neural networks [5]. Deep learning typically refers to very deep networks where many layers of processing are held. These layers of simple non-linear processing units are known as neurons, organized in a feedforward fashion, with all layers being fully connected. With this definition, deep learning encompasses the use of the hidden layers of a feedforward network to learn an interesting and informative representation of the input and the relation that exists between layers. This feature learning ability, to a large extent, has enabled deep learning to gain excellent performance, with seemingly relative ease, on several challenging datasets in various domains [6].

1.1.1 Neural Networks and Deep Learning Architectures

Machine learning is the subfield of AI dedicated to the development of algorithms that can learn from data. In particular, supervised learning is the task of mapping input data to known labels or values, using labeled data to train in such a way that unseen data is used to arrive at the best predictions. Neural networks are models built up by units of artificial neurons that learn from a training algorithm in a way that allows them to map inputs to outputs effectively. Each of the layers of the network receives an input and computes a linear transformation by applying a set of weights to the input and then applying a non-linear function to the result [7]. There are numerous variations of the neural network model where these non-linear functions can also be complex learned functions. Deep learning is a variety of machine learning algorithms that are based on the employment of deep neural networks. The training of deep learning models involves the use of very large amounts of data and parameter tuning, which has only become practical with the advent of deep computer hardware improvements and the massive amounts of data produced in the last two decades. Today, deep learning is the most popular technology for many AI applications, including those related to autonomous vehicles [8]. The subsection further explains deep learning architectures and presents their hardware and software requirements.

1.1.2 Supervised, Unsupervised, and Reinforcement Learning

This searches for various learning strategies in the VANET context and examines their importance and practical viability in the face of different challenges that arise in the domain of AI-enhanced VANETs. There are broadly three universally applicable learning paradigms in the domain of AI, ML, and DL that also find their usage in VANETs:

(1) Supervised Learning: Supervised learning is an important learning paradigm in the machine and deep learning community that involves training algorithms on labeled data. It is being adopted within VANETs to achieve several machine intelligence tasks such as classification, feature extraction, clustering,

and regression. It can be useful in VANETs in several ways where data collected from vehicles is considered as truth/label to supervise the model to learn a beneficial pattern from the vehicular data [9].

(2) Unsupervised Learning: Unsupervised learning is also of critical importance in the community of machine and deep learning. It is being adopted within VANETs to discover valuable insights and patterns from the data that may have no parametric representation or labels. More importantly, it is of specific importance for VANETs in the applications of traffic and mobility-related predictions and optimizations [10].

(3) Reinforcement Learning: A main area of focus of the intelligent transportation community has been to realize environmentally friendly and self-driving or autonomous vehicles where only untethered intelligent systems can achieve autonomous driving. Moreover, under several dynamic real-world traffic conditions, fuel and energy-efficient and semi-decentralized autonomous driving challenges need to be tackled. In such scenarios, vehicles or agents must adapt their decisions based on their knowledge-based model within the limits of either known laws or their experiences from system feedback and the environment [11]. This form of governing decisions and learning is identified as reinforcement learning among popular expert systems in VANETs as illustrated in Fig. 1.

1.1.3 Training and Optimization Techniques

Usually, a computationally effective multilayer perceptron is created when using the combination of region-wise normalization scaling for the initial input, neuron activation functions that are essentially the piecewise continuous nodal functions scaled up according to the function region lengths, and a region-wise normalization scaling for networks representing multilayered neural networks [12]. As scaling is applied to input data and network training aims at the selection of input neuron weights, a neuron that is traditionally realized by wc, so to honor the definition of the activity zone, activation functions should correspond to inverse functions of labeling plane segment balancing involved in radial basis function modeling. After this, when using input data transformation via a scaling procedure inverse to the initially applied scaling, the problem of multimodal cost function for training the network output weights and the catastrophic forgetting problem for replacing initial neuron weights with newly trained ones could be resolved in a way similar to that used in the earlier discussed model containing specialized neuron modules [13].

1.2 Machine Learning in VANETS

An efficient, intelligent vehicle, in essence, comprises the intravehicular structure and the vehicle's interaction with other vehicles, i.e., the Intelligent Transportation

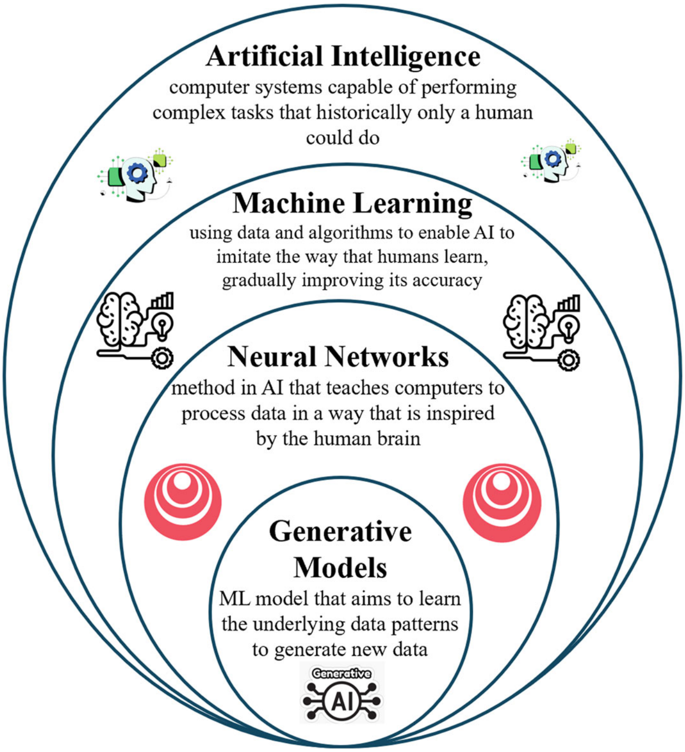
Artificial Intelligence
computer systems capable of performing complex tasks that historically only a human could do
Machine Learning
using data and algorithms to enable AI to imitate the way that humans learn, gradually improving its accuracy
Neural Networks
method in AI that teaches computers to process data in a way that is inspired by the human brain
Generative Models
ML model that aims to learn the underlying data patterns to generate new data
Generative
AI

Fig. 1 Expert systems in VANETs

System. The interactions of the vehicle with the surrounding environment, principally contributions for situational assessment, are challenging and vastly benefit from AI, particularly with the increasing technical and socioeconomic dynamics. Although ITS history has long been focused on communication networks and short-range communication patterns, machine learning techniques are contemporarily also applied to enhance selected ITS fields. One of these advances is intended to prevent crashes by equipping vehicles with wireless communications [14]. As local vegetation and weather conditions can interfere with communication, these systems are hard to securely develop in isolation, spawning unique infotainment and employment challenges. Machine learning within vehicular ad hoc networks can, by means of attaining specialization and improved vehicle matrix estimation, improve situational awareness and vehicle collision warning.

In the vehicle electromobility context, machine learning is investigated by those working with vehicular ad hoc networks. In an exhaustive investigation using VANET, researchers tackle a serious safety issue by fundamentally reducing the rate of discharges per cycle for large and heavy-duty vehicles, which often circulate in the inner city trying to perform their tasks or move goods [15]. Moreover, advanced predictive functions allow drivers or autonomous agents to optimize their resources and deliver smoother operations considerably. Detections of road users and their subsequent paths predict multimodal road user motion and collision risk and, due to the collected data, supervise and adapt purely data-driven estimator interfaces. The architecture of an autonomous vehicle to the traffic control system also supports machine learning models. In addition, statistics have evaluated driving information behaviors in unregulated environments, determining fuel-saving potential. The achieved savings also contributed to a refined accessory model. For the development of a reliable prognostic capability that represents a vital contribution to the targeted electromobility intelligent traffic system, deep reinforcement learning techniques are also employed [16].

1.2.1 Supervised, Unsupervised, and Reinforcement Learning in VANETS

The VANET applications mainly use supervised learning algorithms. Supervised learning is a type of machine learning algorithm; it requires a known set of input data and its corresponding output. It begins with a training phase through the use of labeled input–output pairs, detecting the relationship between input and output. Then, each pair of labeled inputs is forwarded as input to the algorithm, and the output of the algorithm is compared to the labeled outputs to guide the learning. A feedback signal guides the algorithm; the algorithm is adjusted through an iterative process to reduce the differences between the expected and actual outputs. Once trained successfully, the algorithm can give the correct output for an arbitrary input. Supervised learning includes linear regression, logistic regression, support vector machines, and neural networks. The success of supervised learning depends on the anomaly-free detection of the labeled data [4]. Unsupervised learning is based only on the characteristics and features of the input data. Training with labeled inputs and outputs is not needed.

In VANETs, caching algorithms used in certain applications operate by identifying the most important files for caching according to the fluctuating demand of the vehicles; these approaches rely merely on input data alone, thus using unsupervised learning. Therefore, there is no need for training data. A strong unsupervised learning algorithm called reinforcement learning uses an environmental model in which a reactive agent observes an environment by performing actions and is guided by a scalar reward signal. Reinforcement learning is supported by dynamic behavior models such as neural networks, and deep learning models are applied to this issue [8]. In VANETs, reinforcement learning mainly has potential applications in adaptive transportation mode choice, urban traffic flow management, and traffic rerouting. The future most promising use of VANETs spans from reinforcement learning models in urban traffic optimization to big data traffic modeling of urban areas; both campus-scale distributed control loops and deep learning applications for policy-based control of distributed traffic intelligence systems will be in artificial city networks where culture-aware and context-aware belief models will be adapted to the custom design of smart cities [1].

1.2.2 Applications of Machine Learning in VANETS

The dataset of VANETs is built on a series of process simulations and real-life vehicle simulations. One of the key assets of this system, data transmission functionality, is rooted in the dedicated short-range communication standards. In the previous section on machine learning, we discussed some of the many applications of machine learning in route prediction, clustering of vehicles, or global vehicle tracking for network and transmission optimization. One of each vehicle's current key properties to be tracked is its position, relative speed, and direction of other vehicles, or position and speed of the next intersection and its full-range camera visibility. These reports serve as the state of the art for the current role of artificial intelligence in VANET, where its particular utilities and underlying system architecture represent one of only a few primary input sources to a vehicular simulation within an artificial intelligence machine learning process [5]. In short, artificial intelligence in VANET is the primary branch of artificial intelligence-based intelligent transportation systems. Some of the outstanding examples are deep learning-based ensemble models for GPS, the detection and interference in transmission as a result of out-of-sync repeated extended signals, as a byproduct of the intercity road transport cooperative information systems, traffic prediction models resulting from map-reduce clustering algorithms, radio map construction by the use of reference points, the data publisher, and the data buffer maps. Some of the primary work on traffic congestion monitoring, abnormal event detection, and trajectory clustering was performed by time-series embodied transportation datasets [7].

1.3 Challenges in AI-Enhanced VANETS

While the potential for innovation in AI-enhanced VANETs is extensive, the challenges are many and range from fundamental communication and computation issues to complex algorithms. Challenges can be grouped as follows: Smart vehicle design: embedding intelligent behaviors into vehicles, together with reliable low-latency communication with nearby vehicles, will make VANETs more responsive to proactive traffic management or reactive maneuvers and thus enhance safety, creating opportunities for new advanced driver assistance systems and self-driving capabilities [8]. Diverse data types and communication situations: gaining insight and meaningful predictions requires a rich stream of data covering many traffic situations and a range of road users. Consequently, gathering information is a challenge, and this challenge is made more complex due to uncertainty and incomplete communication conditions arising from the effects of weather or significant obstacles around cars that may prevent or rapidly attenuate communications. Rapid inference with large amounts of information: decision-making often involves combining very recent observations with several layers of information, ranging from local information to high-level global statistics on road conditions [13]. Inference must be kept predictable due to safety trends or compliant with the tight latency budget that might be imposed in order to adjust decision-making in case the communication is about to become unavailable. Variability in end-to-end connections from a vehicle to the cloud: variability and congestion on the communication network are difficult to predict, which means that end-to-end latencies from cars to AI engines can be highly variable. Such device issues introduce barriers to commercial deployment, as it would be necessary to simultaneously benefit from short-latency real-time inference while keeping capital expenditures under control [15]. Therefore, all technology needs to be affordable, as it is designed for end users with parallel access.

1.3.1 Security and Privacy Concerns

Security and privacy concerns have drastically increased within VANET environments, as they both pose essential cornerstones for vehicular communication safety. In fact, VANETs need to enable, on the one hand, the revealing of sparse amounts of temporal and spatial vicinities at appropriate times to deliver cooperative collision warnings while avoiding excessive privacy compromises. On the other hand, they must fulfill strong cryptographic privacy and security to protect the different types of VANET data and broadcasts against multiple hostile adversaries across both commercial and large highway VANET deployments [17]. Henceforth, VANET should tolerate a robust form of privacy to allow vehicles to prevent their effective location from being disclosed and disseminate this information securely to establish essential cryptographic keying material. In addition, VANETs also need to maintain V2V communication in order to generate ample relevant information for the roadside warning units. Due to numerous issues that are considered extremely challenging in the scenarios of VANET, whenever the threat cannot be physically detected in a timely manner, this issue arises from being connected with the wireless communication infrastructure [18]. This network infrastructure is constrained to a limited collection of deployed roadside units near the traffic signals. These vulnerable roadside units are reachable by concealed mobile attackers, which enables them to launch numerous advanced attacks. The research community has raised their concerns differently, proposing alternatives to alleviate this problem. However, the reality insists on boosting the fact that several far-ranging issues have yet to be solved [19]. There several legal concerns of associated with the AI and ML when it comes to its application in VANETs, as illustrated in Fig. 2.

1.3.2 Scalability and Resource Constraints

In the real world, the demand for intelligence is not just for general AI-enabled vehicles or smart road infrastructures. In densely connected VANETs, the environmental and spatial learning required by the vehicles and infrastructures in the neighborhood rely on their learning capacities and spatial services. This is where we meet VANETs, which renew the concept of connected intelligence that is only viable at the edge through IoT. VANETs only contain AI-equipped vehicles and structures

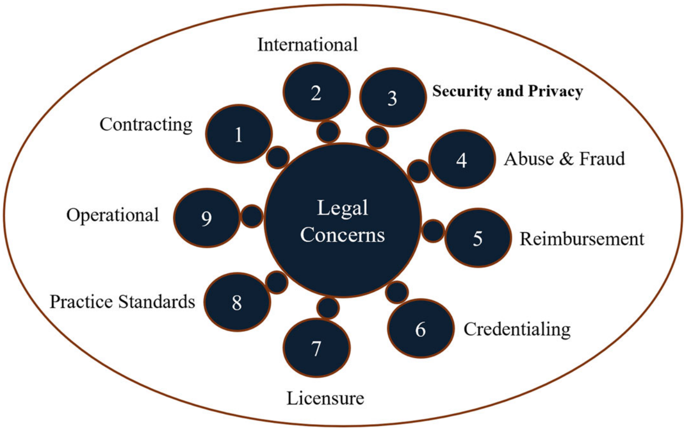

Fig. 2 Legal concerns in using artificial intelligence and machine learning in VANETs

with the necessary computational intelligence to provide intelligent AI services to each other [20]. However, additional AI services at some of the nodes beyond just traffic management should be enabled. In terms of scalability, these are not standard WSNs and no other distributed intelligence network. They are unique problems of VANETs compared to other mobile ad-hoc networks and WSNs. The increasing complexity is now migrating the relevant technology that was initially developed as methods targeted for high-performance servers with a huge amount of dynamic random-access memory to other platforms with limited resources. Deploying the basics of ML/DL and models for mobile systems that have low memory bandwidth and a limited number of parallel processors are the most common attempts to deploy ML/DL at the edge [21].

The operational constraints and physical size are the primary constraints that require methodologies and models for resource-constrained platforms. Deploying deep learning models on hardware devices also leads to new challenges in terms of high memory requirements and computational complexity. High on-device data storage and computational capacity are the main requirements to train and deploy deep learning models on mobile systems. Depending on the training algorithm, training a deep learning model with a small training set on a resource-constrained mobile device might require a substantial amount of computational power and energy. Only the first few layers of a deep learning model can be applied to a mobile device, where the depth of the model and the storage are limited. The actual depth and width of the existing DL models pose an arduous challenge to deploy these models on any low-cost mobile platform [19]. With their demanding applications, such as speech processing and natural language processing, the larger parameter sizes and computations of these deep learning models can inevitably proliferate. These canons exacerbate the difficulty of training a deeper model on a conventional server.

The long execution time makes such training prohibitive for resource-constrained mobile devices, and the tremendous memory overhead inflates the dynamic memory allocation cost. Using deep learning models for mobile scenarios is also arduous, and the models are too large and too complicated. The response time limit for it to be practical is too long, as it takes as much time as the current deployment does. Other resource constraints, like the smaller size of datasets, exist in the model, while training and computation are significant [1]. There are many deficiencies in terms of generalization. Focusing on reducing model complexity while maintaining accuracy is a poignant performance perspective and a recognized model design discipline. Due to the increasing size of data and models, efficient deep learning for the on-device deployment of mobile and Internet of Things AI applications that exhibit resource restrictions is increasingly challenging. These challenge the calculation, size, and energy efficiency of the mobile deep learning model. To build deep neural networks for on-device inferring, training, and learning, these restrictions may require trade-offs between computation and prediction accuracy [5].

1.4 Innovations in AI for VANETS

Enhancing transportation by achieving vehicular ad-hoc network (VANET) autonomous operation is a challenging task. However, several incentives like $5.6 trillion in revenue from mobility services, safety, no traffic jams, time savings, energy savings, comfort auto driving, free parking, and vehicle platooning have encouraged communication tool development. However, many challenges are slowing down the deployment of AI-aided VANETs. In a few vehicular VANET ad-hoc networks, the installed technologies are not accurate in localization, position control, and service quality and must be improved [7]. This work concentrates on the big challenges and the latest advances in machine learning and deep learning technology for updating the position, velocity, and acceleration, as well as the next position, acceleration, and velocity of moving vehicles. Location-based and social network-based services enable movement prediction for private cars and self-driven cars. Autonomous driving services have been developed with image camera radar-based data processing of vehicles' detailed forward and side views. However, these require innovative combinations to achieve general public vehicle autonomous driving, as positioning results expose shortcomings, such as whether the road environment conforms to the actual road environment of the sensors on the car [10]. Buildings or other obstructions on the roadside may cause inter-object occlusions in advance and on car sides, and a planar radar may cause complex modeling of the road-defined slab due to ground discount changes and other reasons.

1.4.1 Edge Computing and Fog Computing in VANETS

The advent of broadband cellular and short-range communication technologies for V2X communications not only provides a powerful tool for vehicle data acquisition, sharing, and processing but also enables edge computing and fog computing services in vehicle cloud computing infrastructure, as vehicles traveling within about 250 m (or 1 s of road traveling on average) can readily connect through vehicle-to-vehicle and vehicle-to-infrastructure communications with communication latency of less than 1.4 ms. Recently, a mesh blockchain mechanism was proposed to enable the coordination and management of public smart parking garages, which effectively addressed the difficulties of vehicle en-route parking but did not include the computation offloading techniques between the parking facilities and the vehicles [22]. Furthermore, research challenges of design, standardization, validation, and deployment remain largely unsolved for the large-scale computation services in VANETs.

Vehicle edge and fog computing are the cornerstones in providing computation offloading services to real-time data analytics and AI-based vehicular applications in VANETs. AI adoption in vehicular networks has largely been confined to vehicles, and most of the AI-based applications in vehicular networks consist of data analytics using telematics, infotainment, driver assistance, etc. The behavior prediction, personalized route planning, environmental perception, cooperative driving, and cooperative sensing applications for all vehicles within communication range will gain great propagation performance benefits with the support of vehicular edge and fog computing [19]. Edge and fog computing not only focus on providing computation services for the large volume and time-sensitive data generated within the communication range but also facilitate edge AI in time-sensitive data analytics and AI-based applications, meaning that only a small percentage of data meeting predefined constraints flow to the cloud/node, whereas the timing operating cycles are crucial due to time-sensitive constraints [23].

1.4.2 Collaborative Learning and Federated Learning

While collaborative learning policies have been proposed to facilitate collaboration among autonomous vehicles in a way that the learning difficulties faced by an autonomous vehicle are distributed to the surrounding vehicles, allowing them to help each other when experiencing difficulties in their learning process, research in AI in VANETs can borrow more techniques and algorithmic solutions from machine learning and artificial intelligence. Collaborative learning occurs at the level of observing the behavior of other agents and trying to infer something more than merely the a priori known map of the environment [15]. This would allow for the sharing of information and leveraging opportunities for mutual improvement in the learning process without the exchange of actual labeled samples. In contrast to collaborative learning, there exist many scenarios where the performance of an agent with limited resources can be significantly improved by initially learning based on input from many other agents with a larger set of resources without requiring the other agents to exchange the learned weights and received labels. When the agents are not allowed to share the complete model or a large number of training data, they can still enjoy a significant performance gain by sharing the publicly or privately learned partial mathematical models from the source agents under privacy constraints on the training data [14]. Some researchers have found that allowing agents to propose alternative simplifications identify weaknesses in the proposed models, and then incorporate preferences and suggestions into the decision-making process improves overall performance.

1.4.3 Intelligent Traffic Management Systems

In an effort to reduce the burden of traffic congestion and fatalities, the concept of intelligent transport systems was introduced. Utilizing artificial intelligence methods and techniques, traffic dynamics and congestion can be identified by analyzing real-time sensed traffic conditions. Intelligent traffic management system applications can be as basic as dynamic traffic light control or permitting/forbidding vehicles to access the road network from one side based on the current traffic load [7]. The emerging intelligent traffic management systems (ITMS) operation seeks to reduce other known problems, mostly peak congestion, through running AI applications providing:

- Much-needed efficiency in traffic flow and operation.
- More than 20% reduction in travel time.
- Safety improvements.
- Investment results in the form of reduced physical infrastructure.

Emerging ITMS application routes are indirectly ingrained with predictive analytics—estimated load flows and congestion occur with the use of machine-learning RouteAVTMs. RouteAVTMs provide intelligent route selection by mining very large databases of historical flow patterns and incidents. Based on the surveys done so far, the estimated origin and potential bottlenecks to destination time are provided. Urban EV/AV first and last-mile navigation fixtures, which rely on real-time information, are classic application instances embedded into the emerging ITMS system design [14]. An intelligent system by which automobiles abide by past road vehicle trajectories, involving instantaneous and past road vehicle movements from nearby vehicles, will operate efficiently by a chance future level of mobility in urban environments. The knowledge of the past road vehicle trajectory reinforced with real-time information makes for a better-informed vehicle so that, ultimately, the at-fault driver, the vehicle, or the road spot is protected. Despite such noticeable advancements in the deployment of AI in enhancing traffic operation, there exist numerous challenges to be addressed in the future of driving intelligence systems [24].

1.5 Case Studies and Practical Implementations

We have chosen two distinct case study scenarios to illustrate the dynamics of learning-enabled spatial traffic control modules inside a VANET: a New Jersey

Distributed Ledger Technology network and a dynamic and autonomous offloading infrastructure network. First, the non-join DLTDB control module is considered within the framework of the NJ queue. With the NJD queue limit, the Prioritizer configures the broadcasting preferences of vehicles to enter and exit New Jersey. The Prioritizer advocates for vehicles to turn or exit outputs, promotes small reward modules and block periods, and maximizes learning [22, 23]. Vehicles that meet the requirements of the overweight NJ queue are ready to enter and wait for the road after a specific RSSI value. After that, the Prioritize module is discarded and is no longer focused on these two vehicles. In the DYNAOFFI control module, we discuss highway on-ramps while considering the local block, average speed, and collision parameters. This work also introduces CARBLIND modes to increase the efficiency of the traffic controller. Educators use this mode to isolate all participating vehicles during collision apoptosis virtually. CARBLIND also modifies the rewards during the patch transfer cycle. By doing so, learners are encouraged to navigate by changing lanes faster than the survivor of the first competitor meeting. A deep reinforcement learning-based traffic control module called the Deep Learning-based Traffic Decision Block uses visible spatial degrees to control vehicle speed and lane transition inside VAS [18, 19]. The DL block dynamically alters the block length of surrounding vehicles, which are within the perception of the vehicle, to provide EL with faster update signals.

1.5.1 Real-World Deployment of AI in VANETS

The deployment of AI and DS in VANETs faces numerous real-world challenges, such as communication latencies, low mobility speed, and low network coverage. One major challenge is that only a few real-world measurements contain real traffic and real vehicles. Moreover, in many cities or countries, real-world measurement using VANETs is illegal because it interferes with the normal operation of traffic lights. Some studies adopted static real topology of a complex urban VANET network for performance evaluations. These topologies are static and cannot reflect the dynamics of real-world traffic. A project simulates real-world traffic, allowing AI and DS developers to evaluate and verify AI models and algorithms in VANET research-related tasks and competitions [1]. During the last two years, many researchers have developed DL-based sign prediction, object detection, segmentation, and multi-target tracking methods related to urban traffic using various datasets. To facilitate performance comparison and development of real-world applications, we summarize the traffic movement of 200 vehicles captured in a 5 km × 5 km area over 4.5 h. The new dataset combined with a dense monocular camera can provide vast amounts of driving images and is in real-world traffic [12, 13]. The dataset can be used to develop traffic flow forecasting algorithms, accident warning systems, and other comprehensive research studies.

1.5.2 Performance Evaluation and Metrics

The performance of network protocols can typically be evaluated by various metrics, which use measurements of the packet success rates, end-to-end delays, and redundant retransmissions. However, in the VANET scenario, some conventional protocols for network evaluation may not be directly applicable because of the significant differences in the defining network characteristics. In general, the performance of databases can be evaluated by different metrics such as throughput. The application layer is mainly concerned with this metric to ensure that the actual data exchange rate achieves a satisfactory value [1]. It is defined as the number of vehicles sending data to other vehicles. Packet Delay: It is mainly defined as the time it takes for a packet to go from the source to the destination during the time interval over the source and destination's transmissions. Packet Delivery Ratio: It is defined as the ratio of data received by the receivers to the data sent by the senders. Jitter (Packet Delay Variation): It is defined as the independent delays associated with the packets. The constant jitter makes the traffic patterns valuable but bursts in packet transmission within a group of applications form a main interest in jitter [6, 7]. End-to-End Delay: The time it takes for a bit to be sent by the sender to the time that the receiver receives it. This metric establishes the relationship between the application and the transport sub-layer through measurement. Despite being a key metric that provides information, routing, protocol, and route discovery influence it. Route Longevity: The time a route stays open from the origin to the destination. In a VANET, such a metric is critical to ensure high overall system performance, especially when data is sent to provide time- or condition-related warnings [23].

1.6 Future Directions and Research Opportunities

We envision more work to utilize driving intelligence technologies for improving VANET operations and other applications related to intelligent transportation systems. At the communications level, information gathered by advanced driving assistance systems can be used to classify the links into different types based on driving pattern classification. Both types of links are static in the sense that the distances between any two vehicles typically do not change largely over some time. Authorities can dispatch a special VANET system that can implement semi-static routing [18]. We believe that such a communication model will be helpful, especially in rural areas or low-traffic volume scenarios. In the more distant future, we speculate that V2V intelligence will be so heavily relied upon to enable driving automation that almost all vehicles will forgo the current sensing apparatus in favor of a universal sensor platform that uses V2V communications. This development of the communications network will directly benefit VANET applications such as crowd-sourced, highly accurate driving information [2].

First, we believe that the idea of using semi-static routing should be validated through more research work. Such work can be either empirical in the form of real-world tests or theoretical in the form of simulations. We hope that future research will cooperate to develop collaboration for autonomous road transportation. We also welcome advanced driving assistance technology research whose focus is on communications enhancement in VANET. Second, VANET security has always been a major research theme—yet driving intelligence technologies such as deep learning and machine learning bring about new or extended threats. For example, wireless signals can be maliciously delayed or transmitted early to cause a deep learning system to detect a fake obstacle. Making use of GPS jammers, attackers can also maliciously alter the driving pattern information [6]. At one level (the vehicle does not match the traffic pattern from others), managers decide that the pattern no longer applies.

Third, even though this survey focuses on how VANET will benefit from driving intelligence technologies, VANET can also be used to collect an extremely large dataset for training driving intelligence technologies. Such reverse engineering has more implications as such intelligent devices may land in automobiles used for public service. More efforts should be spent to probe how connected vehicle dynamics can be utilized to ensure safe and efficient transitions between operational design domains [9, 10]. We hope that future supporters can join in developing a VANET testbed that has an onboard processing element. Last but not least, we hope that policymakers will create a testbed or a global system-based service to allow researchers to test advanced driving assistance systems. But, from a computer science point of view, driving is just a kind of search problem. However, one approach cares about network efficiency first and compromises user satisfaction; another may be too relaxed to make driving convenient [15, 16].

1.6.1 Emerging Technologies and Trends

In-vehicle edge computing may manage the large complexity of AI systems combined with real-time task requirements and actual traffic-aware situational awareness inferring. Deep learning models with small inferences may be used for obstacle detection. PIT methods can improve road safety with traffic light detection by exploiting actual estimated positions for traffic light planning. V2I and lower latency on 5G networks may produce significant benefits in fairness to safety and autonomous driving robustness. Machine learning and deep learning play a key role in the management and optimization of software-defined VANETs [18]. V2I communication technology integrated with 5G effectively reduces service delay and loss, better able to meet the reliability requirements for intelligent transport. Soft computing and system software component frameworks based on constant multiple-thickness facial and eye recognition methods can be used in the integrated system and provide fast, real-time processing.

Experience shows that it meets the design requirements of AI face recognition applications in the intelligent telematics system and also shows that it has good strengths and overall performance [12]. In general, technological innovation in V2X systems is very smooth, and its development trend is in the direction of safe, intelligent, convenient, fast, and rapid. With people's safety awareness becoming stronger, the development and use of V2X technology to produce an intelligent vehicle system have become more important for traffic safety. Noticeably, at the planning and urban development level, the microscopic traffic flow models used are based on reasonable assumptions about driver behavior. To the best of our knowledge, the opportunities and challenges to autonomous vehicles for efficient and fair traffic flow management are the first to pave the way for future work, its added value to the domain, and the impact on both transportation planners and vehicle development stakeholders [22, 23].

1.6.2 Explainable AI and Trustworthiness

Deep learning and machine learning algorithms are increasingly being used in autonomous vehicles, and AI-ethernet extended vehicular ad-hoc networks. At the same time, decision-making power in vehicular applications is becoming increasingly complex due to the use of neural networks and non-linear models. Due to understandable security-related concerns, there is a pressing need to ensure transparency and user-in-the-loop understanding of how decisions are taken so that these AI systems can be trusted. With a clear requirement for safety, integrity, privacy, and security in applications, this further necessitates transparent and accountable decision-making processes [18]. There is also a risk of user discrimination, which—through feedback loops—can amplify biased decisions taken by machine learning algorithms across a vehicular network and between humans and machines. In the application of AI and the implementation of AI-boosted networks, it is essential to identify and mitigate unintended consequences and to provide explanations for the decisions that are supported by relevant evidence or generated by critical reasoning in decision support systems. User experience and explainable standards, normative laws, and regulations will be implemented in the international version of the roadmap [1, 2].

Explainable AI has become an important ground for research, innovation, and market acceptability for AI in transportation. Model frameworks have started to include the satisfaction group to make consumers and users trust reliable AI in autonomous and cooperative intelligent transportation systems. The explanation of AI capabilities and limitations today can help us make more accurate decisions and protect us from harm, including project errors, omissions, and liability problems. In our design framework for intelligent vehicles, we contribute a new proactive approach to the issue of effort in algorithm selection in step I, to change the decision matrix for trustworthiness in algorithm selection based on explainability or analysis of explanation alternatives to a proactive problem and at which trustworthiness level the expert starts to intervene and propose a new decision based on the new explanation technique conducted instead of explainability. In step II, proactivity then directs the choice of which algorithm to use from multiple alternatives with a lower or higher level of trustworthiness defined by the new explainability technique [7].

1.6.3 Open Challenges and Areas for Further Investigation

The rapid advances in machine learning and deep learning for additional driving intelligence in connected and autonomous cars were comprehensively surveyed. The surveyed ML and DL techniques for in-vehicle AI and sensor fusion in vanilla IoT were also extended to the specific V2X automobile network application. The AI-boosted VANET scheme could potentially decrease the vehicle collision rate, make the traffic smoother, and increase the vehicle's throughput. However, AI-enhanced V2X automobile communication network deployment also comes with various challenges. The efficient training of deep learning VANET models requires a substantial number of labeled samples [23, 24]. Unfortunately, labeled data is quite expensive to obtain. The harvesting of real-life data is also time-consuming and poses certain restrictions due to privacy issues. A promising avenue for solving this problem could be adopting the semi-supervised learning algorithm. Additionally, highly reliable deep learning-based VANET applications are necessary to assure the point of acceptance by the end users. Employing an upgradable or swappable CNN accelerator could provide a feasible implementation option. The CNN model induction with superior levels of robustness against adversarial attacks is another urgent research topic. Last but not least, AI-enhanced VANETs supported by 5G C-V2X have demonstrated promising results. Nevertheless, the effective deployment of the 5G NR or LTE-V2X communication network remains a significant issue for traditionally connected autonomous vehicles [3]. Furthermore, the deployment cost will dramatically increase as a massive number of AI-boosted autonomous vehicles are on the roads.

1.7 Conclusion

This study gathers challenges, research directions, and innovations associated with the introduction of AI in VANETs. It describes the role of machine learning and deep learning in transforming ad hoc and delay-tolerant networks into a robust, fast, and intelligent system by utilizing the potential of vehicles in the Internet of Vehicles era. Security, scalability, and privacy challenges in AI-integrated VANETs were discussed, and further research directions toward these domains were mentioned. Moreover, future research challenges and trends that are required for AI-empowered VANETs to be fully operational were also given. Innovative concepts such as edge computing, fog computing, and smart traffic information systems were introduced to cope with the challenges in the implementation of AI on VANET. The motivation to write this study stems from the need for research in the domain of VANETs equipped with AI solutions as a foundation for developing proactive and intelligent cooperation on highways, in smart cities, and on smart roads. The conclusion recapped the purview of this manuscript, leaving readers with a quick insight into the significance of the research. The challenges of security, privacy, and scalability in the implementation of an AI-enhanced VANET are significant enough to command research attention. The proposed design of a vehicle operator number constitutes a discrete improvement, while edge computing moderates the expense of carrying out AI processing. A potential intelligent traffic management center that controls vehicle parking, as well as multiple environmental features and driver assistance solutions, appears feasible, with a predicted trajectory of intelligent traffic advances. However, whether the four stakeholders involved will proceed responsibly and efficiently remains an open question. The incorporation of AI in VANET is, therefore, richly deserving of research and inquiry.

References

1. Abdullah, N.F., Kiat, Y.C., Sing, Y.Y., Nordin, R.: Assisted car platooning and congestion control at road intersections. Int. J. Integr. Eng. **15**(5) (2023). https://doi.org/10.30880/ijie.2023.15.05.030
2. Akinbi, A.O.: Digital Forensics challenges and readiness for 6G Internet of Things (IoT) networks. WIREs Forensic Sci. **5**(6) (2023). https://doi.org/10.1002/wfs2.1496
3. Alhaj, A.A., Zanoon, N.I., Alrabea, A., Alnatsheh, H.I., Jawabreh, O., Abu-Faraj, M., Ali, B.J.A.: Improving the smart cities traffic management systems using VANETs and IoT features. J. Stat. Appl. Probab. **12**(2) (2023). https://doi.org/10.18576/jsap/120207
4. Alkhalidy, M., Taha, M.B., Chowdhury, R., Ould-Slimane, H., Mourad, A., Talhi, C.: Vehicular edge-based approach for optimizing urban data privacy. IEEE Sensors J. **24**(5) (2024). https://doi.org/10.1109/JSEN.2023.3320071
5. Alladi, T., Kohli, V., Chamola, V., Richard Yu, F.: A deep learning based misbehavior classification scheme for intrusion detection in cooperative intelligent transportation systems. Dig. Commun. Netw. **9**(5) (2023). https://doi.org/10.1016/j.dcan.2022.06.018
6. Amari, H., Houda, Z.A.E., Khoukhi, L., Belguith, L.H.: Trust management in vehicular ad-hoc networks: Extensive survey. IEEE Access (2023). https://doi.org/10.1109/ACCESS.2023.3268991
7. Borah, A., Paranjothi, A.: Research issues in false information broadcasting rogue node detection for green VANETs. In: International Symposium on Wireless Personal Multimedia Communications, WPMC (2023). https://doi.org/10.1109/WPMC59531.2023.10338953
8. Amiri, D., Ahmadi, P., Pierre, S.: A soft voting classification model for network traffic prediction in VANET/V2X. In: International Conference on Wireless and Mobile Computing, Networking and Communications (2023). https://doi.org/10.1109/WiMob58348.2023.10187731
9. Duarte, E.K., Erneberg, M., De Freitas, E.P., Bellalta, B., Vinel, A.: SafeSmart 6G: The future of emergency vehicle traffic light preemption. In: International Conference on 6G Networking, 6GNet 2023 (2023). https://doi.org/10.1109/6GNet58894.2023.10317728
10. Hassan, F., Yu, J., Syed, Z.S., Magsi, A.H., Ahmed, N.: Developing transparent IDS for VANETs using LIME and SHAP: An empirical study. Comput. Mater. Continua **77**(3) (2023). https://doi.org/10.32604/cmc.2023.044650
11. Kapu, V.K., Karri, G.R.: Efficient detection and mitigation of rushing attacks in VANETs using RAID: A novel intrusion detection system. J. Comput. Sci. **19**(9) (2023). https://doi.org/10.3844/jcssp.2023.1143.1159
12. Karabulut, M.A., Shahen Shah, A.F.M., Ilhan, H., Khan Pathan, A.-S., Atiquzzaman, M.: Inspecting Vanet from various critical angles—A systematic review. SSRN Electron. J. (2023a)
13. Karabulut, M.A., Shahen Shah, A.F.M., Ilhan, H., Pathan, A.S.K., Atiquzzaman, M.: Inspecting VANET with various critical aspects—A systematic review. Ad Hoc Netw. (2023). https://doi.org/10.1016/j.adhoc.2023.103281
14. Kaur, G., Kakkar, D.: DRIVE: Dual rider-remora optimization for vehicular routing. Peer-to-Peer Netw. Appl. **17**(2) (2024). https://doi.org/10.1007/s12083-024-01638-6

15. Kaushik, P.: Congestion articulation control using machine learning technique. Amity J. Prof. Pract. **3**(01) (2023). https://doi.org/10.55054/ajpp.v3i01.631
16. Lokhande, S.A., Chauhan, N.: SPHA-VC: Secure passengers health assessment via vehicular communications. Microprocess. Microsyst. (2023). https://doi.org/10.1016/j.micpro.2023.104799
17. Manderna, A., Kumar, S., Dohare, U., Aljaidi, M., Kaiwartya, O., Lloret, J.: Vehicular network intrusion detection using a cascaded deep learning approach with multi-variant metaheuristic. Sensors (Basel, Switzerland) **23**(21) (2023). https://doi.org/10.3390/s23218772
18. Shafik, W.: Generative AI for social good and sustainable development. In: Generative AI: Current Trends and Applications, pp. 185–217. Springer Nature, Singapore (2024).https://doi.org/10.1007/978-981-97-8460-8_10
19. Rajput, N.S., Singh, U., Dua, A., Kumar, N., Rodrigues, J.J.P.C., Sisodia, S., Elhoseny, M., Lakys, Y.: Amalgamating vehicular networks with vehicular clouds, AI, and big data for next-generation its services. IEEE Trans. Intell. Transp. Syst. **25**(1) (2024). https://doi.org/10.1109/TITS.2023.3234559
20. Singh, K., Banda, L., Manjul, M.: Advanced Computer Science Applications: Recent Trends in AI, Machine Learning, and Network Security (2023)
21. Tarawneh, M., AlZyoud, F., Sharrab, Y.: Artificial intelligence traffic analysis framework for smart cities. In: Lecture Notes in Networks and Systems, vol. 711, LNNS (2023). https://doi.org/10.1007/978-3-031-37717-4_45
22. Vatsa, A., Agarwal, S., Ranjani, M.: Lane coloration in real time vehicular ad-hoc networks (VANETS). In: 2023 International Conference on Computer Communication and Informatics, ICCCI 2023 (2023). https://doi.org/10.1109/ICCCI56745.2023.10128248
23. Wang, G., Zhou, M., Wei, X., Yang, G.: Vehicular abandoned object detection based on VANET and edge AI in road scenes. IEEE Trans. Intell. Transp. Syst. **24**(12) (2023). https://doi.org/10.1109/TITS.2023.3296508
24. Xia, X., Li, X., Hou, W., Hua, S., Huang, Q.: AI-based efficient wireless technologies and infrastructure-based networks with VANET for smart transportation high performance. Soft. Comput. (2023). https://doi.org/10.1007/s00500-023-08340-4

AI-Driven VANETs: Integrating Deep Learning and Reinforcement Learning for Adaptive Urban Mobility in Smart Cities

Muhammad Ameer Hamza and Fawad Ullah

Abstract The increasing rate of urbanization and the increased need for efficient transportation have highlighted the shortcomings of traditional traffic management. Pre-programmed infrastructure, human observation, and static traffic signals are examples of outdated methods that usually fall short in handling real-time congestion and unpredictable traffic patterns. The constantly evolving needs of modern urban transportation are also not met by them. To solve these problems, cities are utilizing artificial intelligence (AI) and vehicular ad hoc networks (VANETs). This convergence creates adaptable, data-driven frameworks that transform traffic systems. By combining state-of-the-art technologies like deep learning for predictive analytics, reinforcement learning for dynamic signal optimization, and edge computing for real-time data processing, AI-enhanced VANETs increase the capabilities of traffic networks. These clever solutions lessen congestion via anticipating interruptions and proactive traffic rerouting. We are moving from antiquated, inflexible systems to intelligent networks driven by AI. Increasing vehicle communication, improving road safety, and optimizing traffic flow all depend on them. Using case studies and actual data, we demonstrate how AI-powered frameworks speed up route planning and reduce travel delays. They also support sustainable smart city technologies that are scalable. The results demonstrate AI's ability to both address present inefficiencies and pave the way for upcoming advancements in urban transportation.

Keywords AI-driven VANETs · Smart traffic management · Deep learning

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1 Introduction

In an attempt to make their professions easier and overcome the challenges they have faced in the past, people have labored to build technologies across time. The instruments are gadgets with either physical components or extremely sophisticated and ingenious programming. The ability of an object to accurately read a variety of external data that it receives as input and to use machine learning techniques to learn from this data in order achieve certain objectives and duties through adaptive change is known as artificial intelligence, represents one of the methods currently applied in this respect. We are depending more and more on our brains these days to solve challenges that we formerly faced. Consequently, there is a growing interest in understanding the potential impact of intelligence on our future.

Our transportation systems are getting better thanks to artificial intelligence. It helps cars drive themselves and prevent collisions by utilizing cutting-edge technology including artificial immune systems (AIS). Additionally, to increasing transportation efficiency, these strategies open the door for advanced route planning solutions, autonomous systems, and urban traffic management, all of which support more intelligent and sustainable mobility.

As time has gone on, more and more applications have been created to improve transportation through traffic data analysis. Some apps, like Way care, employ Actual traffic information to enhance traffic flow and lessen backlog [1, 2].

Artificial Intelligence (AI) has the ability to improve urban mobility by streamlining processes, increasing efficiency, and solving transportation is-sues in large cities. Here are a few applications for AI:

- Traffic Management: AI-based Traffic Prediction: This method uses AI algorithms to forecast traffic patterns and congestion in order to improve traffic signal timings and dynamically redirect cars.
- Smart Traffic Lights: AI-driven traffic lights that adjust to current traffic patterns to reduce gridlock.
- Public Transportation: Route Optimization: Reducing delays and increasing efficiency, AI algorithms may improve public transportation routes, timetables, and frequency depending on demand patterns.
- Dynamic Public Transit: AI technologies can instantly modify rail and bus routes in response to passenger demand, cutting down on crowding and wait times.
- Autonomous Vehicles: Self-driving automobiles have the potential to improve road space use, reduce accident risks, and simplify traffic patterns.
- Smart Parking Systems: AI uses applications to guide drivers to open parking spaces, reducing traffic from circling cars.
- Data-Driven Urban Design: Planners may prioritize infrastructure projects by utilizing AI to model growth patterns in cities.
- AI-assisted mixed-use zoning optimizes zoning regulations by analyzing commuter data, which lessens the need for long-distance travel.

- Eco-Friendly Transportation: AI coordinates bike/scooter sharing programs and determines the best sites for EV charging stations based on customer requirements [3] (Fig. 1).

In addition to communication and information exchange issues in VANETs, vehicles also use AI-assisted features for various objectives. In Rahman et al. [4], offer a framework for self-diagnostics that includes machine learning methods for vehicle health monitoring. The framework is able to assess the health of vehicles and alert stakeholders to any issues that are found. An important driving force behind AI-based algorithms is the vehicle's ability to sense its environment, comprehend what happens, and respond appropriately. Examples of this include the tracking of drivers' cognitive states [5, 6], and the identification of objects and pedestrians using image data (vehicular perception) [7], such as spatiotemporal traffic prediction for avoiding traffic jams [8], interior localization for self-driving valet parking [9], or the identification of spatial links between seen items to infer accident conditions [10]. For the modeling tasks resulting from the real-world issues, they seek to address, all of these features rely on AI-based algorithms. Neural networks are particularly common for accurately modeling the complex multidimensional data handled in driver characterization and vehicle perception, including image and LIDAR data [11, 12].

Reinforcement learning algorithms have been extensively investigated for autonomous decision making in automobiles. This prospective route to completely autonomous vehicle systems has not been neglected in the contributions in this special Issue. Anzalone et al. assessed the effectiveness of a method that combined curriculum learning with proximal policy optimization over the CARLA driving simulation in the case of [13]. The promising findings across various traffic situations and driving circumstances imply that the suggested combination may be applied to other value-based reinforcement learning systems [12, 14].

Urban mobility challenges—such as congestion, pollution, and safety—require dynamic solutions that traditional systems cannot provide. AI-driven VANETs address these by enabling real-time data exchange between vehicles and infrastructure. For instance, AI algorithms analyze traffic flow from IoT sensors to reroute vehicles during peak hours, reducing emissions [15, 16]. Similarly, ML models predict accident-prone zones using historical collision data, enhancing safety protocols [17]. These capabilities position AI-enhanced VANETs as critical enablers of sustainable smart cities [18, 19].

1.1 VANETs (Vehicular Ad-Hoc Networks)

Vehicular Ad-Hoc Networks (VANETs) are distributed, autonomous communication systems that provide real-time data sharing between automobiles and highway infrastructure (V2I) as well as among cars (V2V) using wireless protocols such as IEEE 802.11p/WAVE. Key applications including emergency alert distribution,

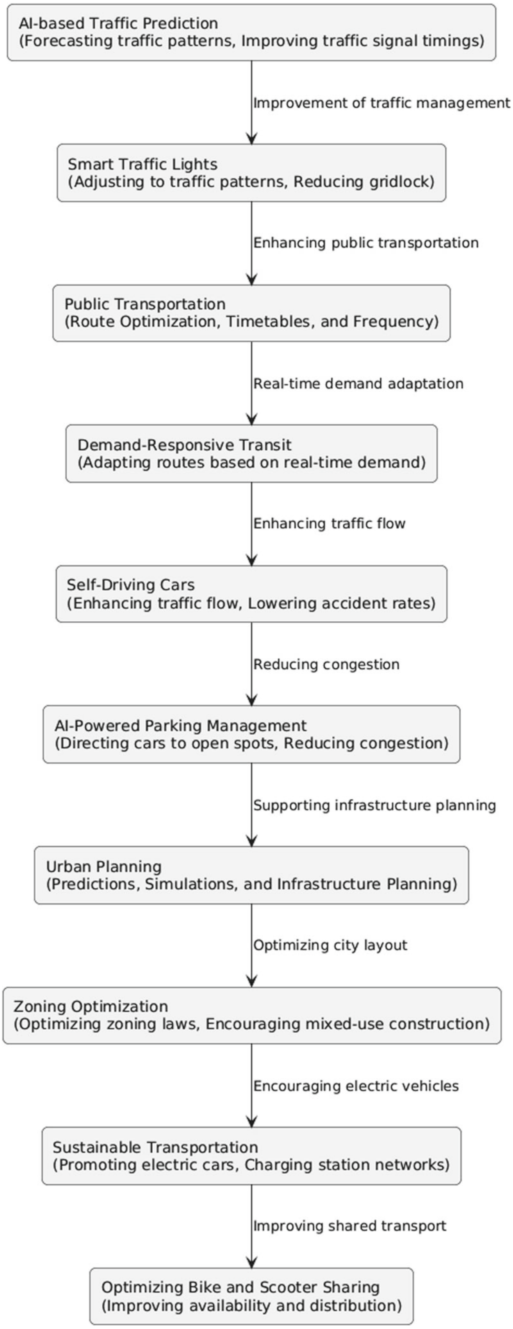
AI-based Traffic Prediction
(Forecasting traffic patterns, Improving traffic signal timings)
Improvement of traffic management
Smart Traffic Lights
(Adjusting to traffic patterns, Reducing gridlock)
Enhancing public transportation
Public Transportation
(Route Optimization, Timetables, and Frequency)
Real-time demand adaptation
Demand-Responsive Transit
(Adapting routes based on real-time demand)
Enhancing traffic flow
Self-Driving Cars
(Enhancing traffic flow, Lowering accident rates)
Reducing congestion
AI-Powered Parking Management
(Directing cars to open spots, Reducing congestion)
Supporting infrastructure planning
Urban Planning
(Predictions, Simulations, and Infrastructure Planning)
Optimizing city layout
Zoning Optimization
(Optimizing zoning laws, Encouraging mixed-use construction)
Encouraging electric vehicles
Sustainable Transportation
(Promoting electric cars, Charging station networks)
Improving shared transport
Optimizing Bike and Scooter Sharing
(Improving availability and distribution)

Fig. 1 AI applications in urban mobility

traffic congestion relief, and accident avoidance are made possible by VANETs, which stand out for their dynamic topology and great mobility. cars can use V2V communication to broadcast road hazard information to other cars in the vicinity, for example, while traffic lights can use V2I coordination to dynamically change the phases of their signals. The capacity of these networks to improve traffic flow and road safety in urban settings makes them the cornerstone of intelligent transportation systems (ITS). Another thorough assessment that highlights the scalability issues with VANETs and their function in enabling adaptive routing algorithms under fluctuating traffic quantities was carried out by Al-Sultan et al. [20].

1.2 Artificial Intelligence (AI)

VANETs stand out for their flexible architecture and ability to control fast-moving vehicles. They enable essential services such as preventing collisions, reducing traffic, and sending out emergency alerts. For instance, automobiles utilize vehicle-to-vehicle (V2V) communication to communicate barriers and other hazards with other nearby vehicles, while traffic lights employ vehicle-to-infrastructure (V2I) connectivity to change their timing. Intelligent transportation systems, which improve the efficiency and safety of city traffic, are built on top of these networks. Research is still being conducted to find out how VANETs may be utilized to alter routes during times of high demand, as they are currently challenging to scale. Al-Sultan et al. [20] looked into these issues in detail.

1.3 Machine Learning (ML)

Machine learning (ML), a significant area of artificial intelligence, uses data-driven models to find trends and improve systems repeatedly. Reinforcement learning (RL) in VANETs helps in traffic signal adaption by analyzing real-time traffic flow. For instance, wait times may be reduced by more than one-third by the use of real-time signal modification utilizing RL algorithms assessed in simulators like CARLA [21, 22].

1.4 Deep Learning (DL)

A specific area of machine learning called deep learning (DL) models intricate correlations in high-dimensional data using multi-layered neural networks, such as CNNs and RNNs. In VANETs, CNNs process LiDAR and camera inputs for object detection (e.g., pedestrians, vehicles), while RNNs predict traffic congestion using spatiotemporal patterns. For example, CNNs achieve 95% accuracy in real-time road anomaly detection [21, 23].

1.5 Reinforcement Learning (RL) in VANETs

Through trial-and-error, Reinforcement Learning (RL) allows systems to learn the best course of action interactions. In VANETs, RL agents at edge nodes optimize traffic signals by rewarding actions that reduce congestion. A proximal policy optimization (PPO) framework reduces intersection waiting times by 30% in simulated urban networks [21, 24].

1.6 Integration with VANET Applications

- CNNs for Object Detection: DL models process LiDAR/camera data to identify obstacles, validated in edge AI frameworks for road anomaly detection [21, 23].
- RNNs for Traffic Prediction: Hybrid models (e.g., BLSTME-CNN) forecast congestion, enabling preemptive rerouting [21, 25].
- RL for Signal Control: Decentralized RL agents optimize traffic signals dynamically, as shown in CARLA simulations [22].

2 Literature Survey

A view is given by A. Arora et al. about the next generation of multi-agent-driven smart city applications. The authors stress that artificial intelligence will have a big influence on the future development of smart cities. In order to enhance the potential and operation of various new urban activites, including vehicle control blockage, they examine how smart agents could collaborate [26]. EA thorough examination of the possibilities, applications, and challenges of edge-AI enabled video analytics in smart cities is carried out by Badidi et al. [15]. The state of AI applications in video analytics is thoroughly evaluated in this study, with a focus on the edge computing paradigm. The authors discuss how advanced computational methods can enhance video analytics in smart city environments, identifying key challenges that must be addressed for effective implementation [15]. Rizwan et al. [27] examine real-time smart traffic control systems in urban settings, focusing on the integration of big data analytics and IoT technologies. Their work provides management of the data that work for the management of the traffic which integrate a framework that leverages actual time sensor data to find traffic flow and reduce blockage due to which remains relevant [27].

Adewopo et al. [17] analyze traffic incident patterns and propose automated systems for accident detection in urban environments. Their work investigates how integrated sensor networks and statistical forecasting methods can reduce collision risks and streamline emergency protocols, emphasizing advancements in urban safety infrastructure [17]. Apolo-Apolo et al. [28] demonstrate a UAV-based framework for agricultural monitoring, employing mathematical frame-works to estimate crop productivity and fruit dimensions. Though focused on agriculture, this research highlights the versatility of analytical tools in addressing challenges across industries.

The interdisciplinary character of AI is highlighted by the use of deep learning in conjunction with UAVs to provide an accurate estimate [28]. The study of Zhao et al. [18] on parallel transit in Transverse adds to the body of literature. The paper highlights the need for parallel transportation networks in smart cities and goes over fundamental ideas and the development of DeCAST. The authors use artificial intelligence (AI) to enhance transportation infrastructure, providing insights into potential opportunities for increased productivity and decreased traffic [18, 29].

In 2019, Rabby et al. investigate IoT applications in a smart traffic control system. The potential integration of IoT technology into traffic management to boost efficiency is thoroughly examined in this paper. The authors explore a variety of IoT-based technologies and their potential effects on traffic monitoring, control, and optimization [30] (Table 1).

Bešinović et al. [31] focus on enhancing efficiency in rail transport through advanced computational methods. While their work centers on railways rather than roadways, it provides insights into the categorization, operational frame-works, and practical applications of data-driven optimization strategies in transportation systems. With an emphasis on computational approaches to improve train operations, the study offers techniques that may have an impact on more extensive advancements in mobility infrastructure [31].

Yang and associates provide a visual end-edge-cloud structure in a 2023 article that is tailored for low-carbon, 6G-enabled urban networks. With a focus on scalable solutions for smart city connection, their study investigates how automation might be included into next-generation communication systems. Through effective resource allocation and data transmission, the study emphasizes how adaptive network architectures may promote sustainable urban growth [19].

Similar to this, Cui et al. [32] look at how big data analytics may be used to manage autonomous car systems in smart cities. They examine how real-time data processing might improve vehicle coordination by tackling issues like latency and system dependability using the concepts of network calculus. Their research clarified the relationship between vehicle automation and predictive modeling in dynamic urban settings [32].

Additionally, SCOPE, a cooperative system designed to maximize urban parking allocation, is introduced by Alarbi and associates [33]. Through better parking availability and effective driver guidance, this architecture uses sensor networks and real-time analytics to lessen traffic congestion. This approach illustrates how automated resource management might enhance urban transportation without identifying any specific technology [33].

Table 1 The application of deep learning on vanet and their limitations [29]

Ref	Year	Technologies and protocols	Summary	Limitations
22	2021	Technologies: AI Protocols: protocols for data transmission Algorithms utilized: using the GGEN scheduling algorithm and the block matching approach	Gives a summary of intelligent car tracking and detection. and performed well	There is little discussion of implementation challenges in the actual world
23	2023	Smart energy management in smart cities is a major emphasis of the study. It highlights the confluence of digital, communication, and data analytics technologies, although it doesn't specify any particular technologies or approaches	The study emphasizes how technology has the potential to completely transform urban life. It focuses on providing residents with easily accessible services using data-driven methods. The report provides information on current and upcoming smart city potential	Regretfully, the report's shortcomings are not stated clearly. Like any research project, though, it may run into problems with data privacy, unequal access to technology, and the requirement for cross-sector cooperation
24	2023	Wi-Fi access point, sensors, cameras, machine learning, and the internet of things	Uses sensors and social media data to track the movement of cars and pedestrians. Reduces congestion by modifying traffic lights based on real-time data. AI optimizes flow by analysing traffic patterns	Finding the ideal balance between the costs associated with data collection and data quality is still a challenge
25	2022	IoT, 5G, AI, and ML technologies; protocols: TLS/SSL, IPsec, and SSH algorithms Utilized: The Advanced Encryption Standard (AES) and the Triple Data Encryption Standard (3DES)	Less traffic, quicker commuting, and resource savings. Enhances traffic flow by adapting to shifting conditions. tackles a variety of urban transportation issues	Deployment on a large scale might be challenging. Sensors may not be dependable all the time. It might be challenging to integrate the technology with the existing infrastructure
26	2021	Technologies: real-time traffic monitoring, IoT, and artificial intelligence Procedures: data transmission algorithms for traffic pattern analysis and traffic signal management were utilized	Gathering information from social media, smartphone sensors, and cameras. In order to predict congestion, AI and machine learning analyse traffic trends. traffic changes made dynamically to enhance flow	Scalability, sensor dependability, and integration with current infrastructure are implementation challenges

Koshnicharova et al. [34] develop interactive crowd management tools for metaverse applications through dynamic data analysis. Although their research focuses on virtual settings, the spatial optimization and behavioral pattern recognition concepts they cover may help manage real-world crowds at events or transportation hubs, which would help with traffic-related issues [29, 34].

The study contributes a novel framework that integrates edge computing with hybrid deep reinforcement learning (DRL) to address latency and scalability challenges in VANETs. Unlike prior studies [18, 27], our approach combines spatiotemporal traffic prediction (using LSTM networks) with decentralized RL agents at edge nodes, enabling real-time signal optimization while reducing dependency on centralized cloud systems. Additionally, we propose a cybersecurity protocol for VANETs using blockchain-based authentication, addressing a gap identified in [35, 36].

3 Evolution of Traffic Management Systems

3.1 Traditional Methods

For decades, traffic management has relied on basic tools like traffic signals, surveillance cameras, and manual monitoring. While these methods provide a foundational level of control, they often lack the flexibility needed to handle complex, real-time traffic situations efficiently. Traditional systems aren't equipped to respond dynamically to changing traffic conditions, which leads to inefficiencies and increased congestion [37].

3.2 Emerging Technologies

With the advent of new technologies, traffic control has transformed significantly through the penetration of cloud computations, artificial intelligence, and the Internet of Things. These advancements make it possible to create responsive urban transportation solutions by analyzing actual time information streams, predicting congestion patterns, and dynamically adjusting traffic coordination using adaptive systems. The shift from rigid, pre-programmed signal systems to adaptable, data-driven frameworks has greatly improved traffic efficiency and reduced bottlenecks in cities [38].

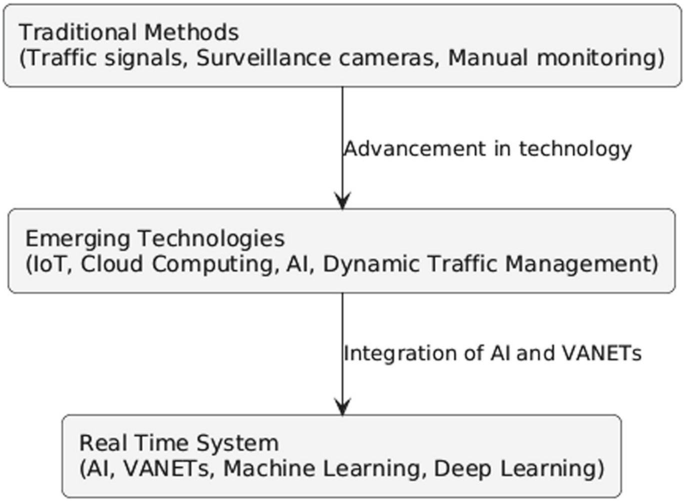
Traditional Methods
(Traffic signals, Surveillance cameras, Manual monitoring)
Advancement in technology
Emerging Technologies
(IoT, Cloud Computing, AI, Dynamic Traffic Management)
Integration of AI and VANETs
Real Time System
(AI, VANETs, Machine Learning, Deep Learning)

Fig. 2 Evolution of traffic management systems

3.3 Real Time System

Integrating advanced computational frameworks into Vehicular Ad-Hoc Networks (VANETs) has enhanced their ability to anticipate traffic disruptions and minimize collision risks. By leveraging real-time data analysis and statistical modeling, modern VANETs efficiently process large-scale traffic datasets, enabling rapid communication between vehicles and infrastructure. These systems support collaborative decision-making protocols to streamline traffic routing and improve road safety outcomes [39] (Fig. 2).

4 AI-Driven Solutions in VANETs

4.1 Deep Learning for Traffic Prediction

By analyzing historical trends and live data, AI predicts congestion hotspots hours in advance. Cities like Los Angeles use these models to preemptively adjust signals during rush hour [40].

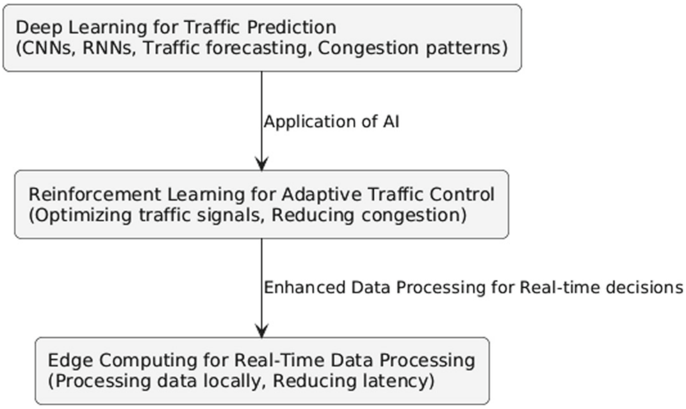
Deep Learning for Traffic Prediction
(CNNs, RNNs, Traffic forecasting, Congestion patterns)
Application of AI
Reinforcement Learning for Adaptive Traffic Control
(Optimizing traffic signals, Reducing congestion)
Enhanced Data Processing for Real-time decisions
Edge Computing for Real-Time Data Processing
(Processing data locally, Reducing latency)

Fig. 3 AI-driven solutions in VANETs

4.2 Reinforcement Learning for Adaptive Traffic Control

Traffic lights "learn" from real-time vehicle density, optimizing green/red cycles to keep traffic moving. Trials in Pittsburgh reduced idle time at intersections by 26% [41].

4.3 Edge Computing for Real-Time Data Processing

In vehicle communication systems, handling data locally at on-site infrastructure reduces delays, allowing for quick adaptation to sudden changes in traffic conditions. By focusing on local data analysis rather than centralized computation, these systems remain responsive, which is crucial for making real-time decisions. Processing data locally (via roadside sensors) instead of sending it to distant servers minimizes delays. This is critical for emergency vehicles needing priority access [42] (Fig. 3).

5 Conclusion

The shift from traditional traffic management to AI-enhanced Vehicular Ad-Hoc Networks (VANETs) marks a significant advancement in tackling the complex challenges of urban mobility. Old methods relied on static signals and manual oversight. They suffered from inefficiencies like unresponsive congestion management, longer travel times, and limited adaptability to real-time disruptions. By integrating AI technologies such as machine learning, deep neural networks, and decentralized edge computing, we've transformed these systems. Now, dynamic, self-learning systems process vast datasets and make split-second decisions.

Deep learning algorithms analyze historical and real-time traffic patterns to forecast congestion accurately. This enables proactive adjustments to signal timings and route recommendations. Reinforcement learning enhances adaptability even further. Signal cycles are repeatedly improved by traffic control systems using real-time vehicle density, meteorological data, and accident reports. Experiments in places like Los Angeles and Pittsburgh have produced remarkable outcomes. There has been a 21% decrease in peak-hour traffic and a 26% reduction in junction delays. By using IoT devices and roadside sensors to handle vital data locally, edge computing guarantees low latency. This is essential for preventing crashes and giving the first importance to emergency cars.

VANETs are at the heart of these developments. They provide seamless communication between infrastructure, vehicles, and central control hubs. By incorporating predictive modeling into VANET frameworks, cities can instantly adjust to the weather, traffic volumes, and road closures. This increases safety and efficiency. For example, in experimental projects, rerouting recommendations and real-time risk alarms sent over VANETs have reduced the likelihood of accidents by up to 18%. However, the broad use of AI-driven systems is hampered by a number of factors. Lack of standardized regulatory frameworks, cybersecurity vulnerabilities, and expensive infrastructure all hinder scalability. Modernizing old urban infrastructure with smart technology is expensive. It's critical to address ethical issues in the integration of automatic cars and to increase the capabilities of edge computing. Creating intelligent transportation networks will be essential as cities continue to change. It is necessary to build inclusive, flexible, and resilient urban settings.

References

1. Nikitas, A., Michalakopoulou, K., Njoya, E.T., Karampatzakis, D.: Artificial intelligence, transport and the smart city: definitions and dimensions of a new mobility era. Sustainability **12**, 2789 (2020). https://doi.org/10.3390/su12072789
2. Lungu, M.: Smart urban mobility: the role of AI in alleviating traffic congestion. In: Proceedings of International Conference and Business Excellence, vol. 18, no. 4, pp. 1441–1452 (2024)
3. Samaei, S.R.: A comprehensive algorithm for AI-driven transportation improvements in urban areas. In: 13th International Engineering Conference on Advanced Research in Science and Technology (2023). https://civilica.com/doc/1930041
4. Rahman, Md.A., et al.: A secure and intelligent framework for vehicle health monitoring exploiting big-data analytics. IEEE Trans. Intell. Transp. Syst. Early. Access 4 Jan 2022. https://doi.org/10.1109/TITS.2021.3138255
5. Ahmed, M., Masood, S., Ahmad, M., Abd El-Latif, A.A.: Intelligent driver drowsiness detection for traffic safety based on multi CNN deep model and facial subsampling. IEEE Trans. Intell. Transp. Syst. Access 22 Dec 2021. https://doi.org/10.1109/TITS.2021.3134222
6. Lv, C., Nian, J., Xu, Y., Song, B.: Compact vehicle driver fatigue recognition technology based on EEG signal. IEEE Trans. Intell. Transp. Syst. Early Access 8 Nov 2021. https://doi.org/10.1109/TITS.2021.3119354

7. Xu, H., Guo, M., Nedjah, N., Zhang, J., Li, P.: Vehicle and pedestrian detection algorithm based on lightweight Yolov3-promote and semi-precision acceleration. IEEE Trans. Intell. Transp. Syst. Early Access 4 Jan 2022. https://doi.org/10.1109/TITS.2021.3137253
8. Dai, F., Huang, P., Mo, Q., Xu, X., Bilal, M., Song, H.: St-Innet: deep spatio-temporal inception networks for traffic flow prediction in smart cities. IEEE Trans. Intell. Transp. Syst. Early Access 10 Jun 2022. https://doi.org/10.1109/TITS.2022.3179789
9. Lei, J., Huang, J., Kong, L., Chen, G., Khan, M.K.: Defloc: deep learning assisted indoor vehicle localization atop FM fingerprint map. IEEE Trans. Intell. Transp. Syst. Early Access 6 Apr 2022. https://doi.org/10.1109/TITS.2022.3163539
10. Zhou, Z., Dong, X., Li, Z., Yu, K., Ding, C., Yang, Y.: Spatio-temporal feature encoding for traffic accident detection in Vanet environment. IEEE Trans. Intell. Transp. Syst. Early Access 15 Feb 2022. https://doi.org/10.1109/TITS.2022.3147826
11. De Sousa, P.H.F., et al.: Intelligent 3d objects classification for vehicular Ad Hoc network based on Lidar and deep learning approaches. IEEE Trans. Intell. Transp. Syst. 6 Apr 2022. https://doi.org/10.1109/TITS.2022.3163539
12. Gupta, B.B., Agrawal, D.P., Sajjad, M., Sheng, M., Del Ser, J.: Guest editorial artificial intelligence and deep learning for intelligent and sustainable traffic and vehicle management (VANETs). IEEE Trans. Intell. Transport. Syst. **23**(10), 19575–19577 (2022)
13. Anzalone, L., Barra, P., Barra, S., Castiglione, A., Nappi, M.: An end-to-end curriculum learning approach for autonomous driving scenarios. IEEE Trans. Intell. Transp. Syst. Early Access 26 May 2022. https://doi.org/10.1109/TITS.2022.3160673
14. Raja, G., Anbalagan, S., Senthilkumar, S., Dev, K., Qureshi, N.M.F.: SPAS: smart pothole-avoidance strategy for autonomous vehicles. IEEE Trans. Intell. Transp. Syst. Early Access 13 Apr 2022. https://doi.org/10.1109/TITS.2022.3161589
15. Badidi, E., Moumane, K., Ghazi, F.E.: Opportunities, applications, and challenges of edge-AI enabled video analytics in smart cities: a systematic review. IEEE Access **11**, 80543–80572 (2023). https://doi.org/10.1109/ACCESS.2023.3300658
16. Gharrawi, H.A., Yaghoub, M.B.: Traffic management in smart cities using the weighted least squares method (2022). Arxiv Preprint ARXIV:2205.00346
17. V. Adewopo, N. Elsayed, Elsayed, Z., Ozer, M., Wangia-Anderson, V., Abdelgawad, A.: AI on the road: a comprehensive analysis of traffic accidents and autonomous accident detection system in smart cities. In: 2023 IEEE 35th International Conference on Tools with Artificial Intelligence (Ictai), Atlanta, GA, USA, pp. 501–506 (2023).https://doi.org/10.1109/ICTAI59109.2023.00080
18. Zhao, C., Wang, X., Lv, Y., Tian, Y., Lin, Y., Wang, F.-Y.: Parallel transportation in transverse: from foundation models to DeCAST. IEEE Trans. Intell. Transp. Syst. **24**(12), 15310–15327 (2023). https://doi.org/10.1109/TITS.2023.3311585
19. Yang, Z., Hu, D., Guo, Q., Zuo, L., Ji, W.: Visual E2c: AI-driven visual end-edge-cloud architecture for 6g in low-carbon smart cities. IEEE Wireless Commun. **30**(3), 204–210 (2023). https://doi.org/10.1109/MWC.019.2200518
20. Al-Sultan, S., et al.: A comprehensive survey on vehicular Ad Hoc networks. J. Network Comput. Appl. **37**, 380–392 (2014).https://doi.org/10.1016/J.JNCA.2013.02.036
21. Pradeep, R., Revathi, K., Thomas, A.K., Srikanth, R.: A novel optimized AI based model for traffic prediction in VANET. In: 2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA), pp. 1175–1180. IEEE (2023)
22. Kandali, K., Bennis, L., El Bannay, O., Bennis, H.: An intelligent machine learning based routing scheme for VANET. IEEE Access **10**, 74318–74333 (2022)
23. Khatri, S., Vachhani, H., Shah, S., Bhatia, J., Chaturvedi, M., Tanwar, S., Kumar, N.: Machine learning models and techniques for VANET based traffic management: implementation issues and challenges. Peer-Peer Netw. Appl. **14**, 1778–1805 (2021)
24. Teixeira, D., Ferreira, J., Macedo, J.: Systematic literature review of AI/Ml techniques applied to VANET routing. In: Future of Information and Communication Conference, pp. 339–361. Springer, Cham (2022)

25. Ouhmidou, H., Nabou, A., Ikidid, A., Bouassaba, W., Ouzzif, M., El Kiram, M.A.: Traffic control, congestion management and smart parking through VANET, Ml, and IoT: a review. In: 10th International Conference on Wireless Networks and Mobile Communications (WINCOM), pp. 1–6. IEEE (2023)
26. Arora, A., Jain, A., Yadav, D., Hassija, V., Chamola, V., Sikdar, B.: Next generation of multi-agent driven smart city applications and research paradigms. IEEE Open J. Commun. Soc. **4**, 2104–2121 (2023). https://doi.org/10.1109/OJCOMS.2023.3310528
27. Rizwan, P., Suresh, K., Babu, M.R.: Real-time smart traffic management system for smart cities by using internet of things and big data. In: 2016 International Conference on Emerging Technological Trends (ICETT), Kollam, India, pp. 1–7 (2016). https://doi.org/10.1109/ICETT.2016.7873660.LI. Wang, X., Zhan, Q., Liu, Y.: Lightweight deep learning-based fruit identification for real-time applications. Comput. Electron. Agric. **189**, 106420 (2021)
28. Apolo-Apolo, O.E., Guanter, J.M., Egea, G., Raja, P., Perez-Ruiz, M.: Deep learning algorithms for estimate of the production and size of citrus fruits utilizing a UAV. Eur. J. Agron. **115**, 126030 (2020). https://doi.org/10.1016/J.EJA.2020.126030
29. Chavhan, R.D., Sambare, G.B.: AI-driven traffic management systems in smart cities: a review. Educ. Adm.: Theory Pract. **30**(5), 105–116 (2024)
30. Rabby, M.K.M., Islam, M.M., Imon, S.M.: A review of IoT application in a smart traffic management system. In: 5th International Conference on Advances in Electrical Engineering (ICAEE), Dhaka, Bangladesh, pp. 280–285 (2019).https://doi.org/10.1109/ICAEE48663.2019.8975582
31. Besinovic, N., et al.: Artificial intelligence in railway transport: taxonomy, regulations, and applications. IEEE Trans. Intell. Transport. Syst. **23**(9), 14011–14024 (2022). https://doi.org/10.1109/TITS.2021.3131637
32. Cui, Q., et al.: Big data analytics and network calculus enabling intelligent management of autonomous vehicles in a smart city. IEEE Internet Things J. **6**(2), 2021–2034 (2019). https://doi.org/10.1109/JIOT.2018.2872442
33. Alarbi, M., Jaradat, A., Lutfiyya, H., Haque, A.: Scope: smart cooperative parking environment. IEEE Access **11**, 120346–120361 (2023). https://doi.org/10.1109/ACCESS.2023.3328233
34. Koshnicharova, D., Mihovska, N.A., Koleva, P., Poulkov, V.: Data-driven interactive crowd management systems for metaverse scenarios. In: 25th International Symposium on Wireless Personal Multimedia Communications (WPMC), Herning, Denmark, pp. 549–554 (2022).https://doi.org/10.1109/WPMC55625.2022.10014794
35. Shaimaa, A.H., Zaki, A.E.: A fog based smart traffic management system. Nile J. Commun. Comput. Sci. **3**(1), 1–16 (2022)
36. Lilhore, U.K., et al.: Design and implementation of an ML and IoT based adaptive traffic-management system For smart cities. Sensors **22**(8), 2908 (2022)
37. Rabby, M.K.M., Islam, M.M., Imon, S.M.: A review of Iot application in a smart traffic management system. In: 5th International Conference on Advances in Electrical Engineering (ICAEE) (2019). https://doi.org/10.1109/ICAEE48663.2019.8975582
38. Cui, Q., et al.: Big data analytics and network calculus enabling intelligent management of autonomous vehicles in a smart city. IEEE Internet Things J. (2019).https://doi.org/10.1109/JIOT.2018.2872442
39. Ben Youssef, M., Salhi, A., Ben Salem, F.: Intelligent multiple vehicle detection and tracking using deep-learning and machine learning: an overview. In: 18th International Multi-Conference on Systems, Signals and Devices (SSD) (2021).https://doi.org/10.1109/SSD52085.2021.9429331
40. Zhao, C., Wang, X., Lv, Y., Tian, Y., Lin, Y., Wang, F.-Y.: Parallel transportation in transverse: from foundation models to Decast. IEEE Trans. Intell. Transport. Syst. (2023).https://doi.org/10.1109/TITS.2023.3311585
41. Besinovic, N., et al.: Artificial intelligence in railway transport: taxonomy, regulations, and applications. IEEE Trans. Intell. Transport. Syst. (2022).https://doi.org/10.1109/TITS.2021.3131637

42. Yang, Z., Hu, D., Guo, Q., Zuo, L., Ji, W.: Visual E2C: AI-driven visual end-edge-cloud architecture for 6g in low-carbon smart cities. IEEE Wirel. Commun. (2023). https://doi.org/10.1109/MWC.019.2200518

Innovative Approaches to Urban Planning and Sustainable Development: The Role of AI-Driven Vanets in Smart Cities

Muhammad Usama, Ubaid Ullah, Zaid Muhammad, Muhammad Abbas, Muhammad Ameer Hamza, Muhammad Rouf, and Muhammad Bilal

Abstract Sustainable development and urban planning are essential to creating resilient, just, and ecologically conscientious cities. This chapter examines cutting-edge urban planning techniques that combine sustainability, community involvement, and technology developments, emphasizing the revolutionary potential of AI-powered Vehicular Ad-hoc Networks (VANETs). By facilitating real-time communication between infrastructure and automobiles, VANETs enhance traffic control, ease congestion, and cut carbon emissions. The chapter also covers how data-driven decision-making and predictive analytics improve urban mobility, maximize resource allocation, and support the objectives of smart, sustainable cities. The chapter emphasizes the significance of all-encompassing, flexible techniques for long-term sustainability by looking at the role of AI in urban ecology, public transportation networks, and renewable energy integration. Through innovation and collaboration, urban planners and policymakers can leverage AI and VANET technologies to create livable, urban landscapes that are sustainable for both current and forthcoming generations.

Keywords Urban planning · Sustainable development · Smart cities · VANETs · Artificial intelligence · Urban sustainability

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1 Introduction

There is a pressing need and opportunity to reconsider how we build and run our cities as a result of growing environmental consciousness and concern, urbanization, and technological advancement. In recent decades, these interconnected Under The updated term “smart sustainable cities”, concerns and developments have begun to come together [1]. In this chapter, the concept of “smart sustainable cities” is introduced and discussed. Additionally, the chapter attempts to define “smart sustainable cities” and lists some of the primary challenges to implementing the concept. Smart cities and sustainable cities are defined in a variety of ways, but their relationship has not gotten as much attention. In addition, because the terms “smart city” and “sustainable city” have different connotations, it is challenging to mix them. To promote a common understanding of the concept and provide a starting point for future discussions on the advantages that smart sustainable cities are supposed to provide, a definition of smart sustainable cities is necessary [2].

The sustainability movement has resulted in a new approach to urban planning during the past few decades. Planners are putting more focus on social justice and environmental sustainability. This shift is seen in the growing emphasis on open spaces, public transportation, mixed-use complexes, and community involvement. The historical history of urban planning gives a vital insight of the current trends and future potential in the discipline [2] (Table 1).

The main objective of this chapter is to equip policymakers, urban planners, and other stakeholders with the knowledge and resources necessary to create cities that can flourish amid rapidly increasing urbanization and global environmental changes. By adopting innovation and sustainability, Urban areas can be developed to improve the well-being of generations to come, making certain that our cities continue to be lively, resilient, and enduring centers of human endeavor.

2 Importance of Sustainable Development

The concept of sustainable development aims to reconcile various, sometimes conflicting goals while recognizing the social, economic, and environmental constraints that our society faces. It signifies satisfying current needs without jeopardizing future generations’ capacity to fulfill theirs. Considering that ecosystems and natural resources often face challenges due to the swift rate of urbanization and development, this idea is crucial for urban planning. Sustainable development guarantees that social equity, ecological conservation, and economic advancement are advanced concurrently, fostering a comprehensive strategy for growth [18, 19]. In urban planning, sustainable development seeks to establish urban environments that are environmentally friendly, financially practical, and socially inclusive. This includes utilizing green infrastructure, like parks and green roofs, to improve urban

Table 1 Standard techniques used in innovative approaches to urban planning and sustainable development, along with a description, limitations

References	Technique used	Description	Limitations
[3]	Internet of Things (IoT)	IoT implementation for effective management of cities, including control of traffic, trash management, and smart grids	High initial costs, privacy concerns, and data security issues
[4]	Vertical gardens and green roofs	Integration of vertical gardens and green roofs in urban buildings to enhance air quality, reduce heat islands, and promote biodiversity	High maintenance costs and structural load considerations
[5]	Transit-oriented development (TOD)	Development of urban areas centered around public transport hubs to reduce reliance on cars and promote sustainable commuting options	Potential for increased property prices and gentrification
[6]	Participatory design workshops	Including the community in the planning process to guarantee that developments satisfy local requirements and tastes	Time-consuming process and potential conflicts among stakeholders
[7]	Brownfield redevelopment	Reclaiming and redeveloping contaminated industrial sites for new urban uses, thereby reducing urban sprawl and preserving greenfield	High cleanup costs and potential legal challenges
[8]	Form-based codes	Implementing form-based codes to regulate land development and create predictable urban forms that support sustainability	Requires significant changes to existing zoning laws and regulations
[9]	Climate adaptation strategies	Creating urban planning techniques that increase cities' ability to withstand the consequences of global warming, including floods and extreme temperatures	Uncertain future climate scenarios and high implementation costs
[10]	Autonomous vehicles	Integrating driverless cars to improve accessibility and safety in cities while lowering pollution and traffic jams	Technological, legal, and ethical challenges
[11]	Renewable energy integration	Integrating energy from sustainable sources, including wind and solar power, into metropolitan infrastructure to reduce emissions of carbon and promote independence from electricity	Intermittency issues and high initial investment costs
[12–14]	Predictive analytics	Utilizing AI and using large-scale data insights to forecast urban planning and manage urban growth, resource allocation, and infrastructure needs	Issues with data privacy as well as the requirement for big datasets and powerful computers

(continued)

Table 1 (continued)

References	Technique used	Description	Limitations
[15]	Disaster risk reduction	Designing urban areas to be resilient to natural disasters through adaptive infrastructure and emergency preparedness plans	High costs of retrofitting existing infrastructure and potential resistance from local communities
[16, 17]	Affordable housing initiatives	Creating policies and programs to ensure affordable housing in urban areas to promote social equity and prevent displacement due to gentrification	Financial constraints and opposition from developers and existing residents

biodiversity and lessen environmental effects [20]. Sustainable urban planning prioritizes effective public transport networks and renewable energy solutions to minimize carbon emissions and enhance energy efficiency [21, 22].

2.1 Objectives of Urban Planning and Sustainable Development

Through the use of technology, smart city urban planning places a high priority on sustainability, efficiency, and quality of life. It improves services such as transportation, waste management, and energy distribution using data analytics and IoT. Key objectives include lowering carbon footprints, boosting renewable energy, increasing public transportation, and developing green space. Social inclusion guarantees access to housing, healthcare, and internet connectivity. Innovation clusters, startups, and digital infrastructure support economic growth, increasing global competitiveness and resilience [23, 24].

2.2 Principles of Sustainable Development

The goal of sustainable development is to balance economic advancement, environmental preservation, and social inclusion. Moreover, now it guarantees that the current requirements are fulfilled without jeopardizing future generations' capacity to satisfy theirs, which necessitates strategic planning and effective resource management. Promoting equitable and vigorous economic growth improves community well-being by providing inclusive possibilities. Effective resource use reduces waste and environmental effect through recycling and sustainable technology. Furthermore, developing resilient structures and systems improves the ability to endure environmental, social, and economic problems [25].

2.3 Urban Ecology and Environmental Psychology

Urban ecology studies the relationships between living creatures and their urban environments. It investigates the effects of urbanization on ecological systems and aims to create urban environments that support biodiversity and ecosystem function. Urban ecologists study how plants, animals, and microbes adapt to urban environments and how urban design might enhance ecological well-being [26].

Environmental Psychology examines the relationships between individuals and their environments. It explores the influence of urban settings on mental health, behavior, and overall well-being [27]. Main areas of focus consist of: Space Perception: The way people perceive and engage with urban environments, encompassing the impact of design features on feelings and actions [28]. Social Interactions: The impact of city settings on social conduct, community involvement, and social unity [29]. Stress and Well-Being: The influence of urban design elements, like noise, population density, and access to green areas, on stress levels and overall health [30]. Incorporating knowledge from urban ecology and environmental psychology into urban planning can create spaces that promote ecological sustainability while also enhancing human health and well-being.

2.4 The Role of Landscape Architecture in Urban Planning

Landscape architecture is vital in urban planning as it involves designing and managing outdoor areas to improve aesthetic appeal, functionality, and environmental quality. Landscape architects engage in diverse projects, such as parks, public squares, waterfront areas, and urban green spaces [31].

Their work involves, Designing appealing and practical public areas that encourage social connections, leisure activities, and community involvement [18]. Implementing green infrastructure concepts, green roofs and rain gardens, for example, to control runoff, enhance air quality, support urban biodiversity. Restoring impoverished urban regions and rehabilitating natural environments to enhance ecological well-being and sustainability [18, 19] Integrating artistic features and cultural allusions into landscape designs to represent local identity and improve the character of urban environments [20].

3 Innovative Urban Planning Strategies

3.1 Smart Cities and Technology Integration

3.1.1 AI-Driven VANETs in Urban Management

The incorporation of AI technologies in Vehicular Ad-hoc Networks (VANETs) is a remarkable improvement in smart city development. VANETs operates on vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, which allows urban transportation systems to operate more efficiently through real time data exchange. These networks use AI technologies to forecast traffic, suggest optimal routes, and control traffic flows. For example, AI algorithms can change traffic signals to dynamically optimize the movement of cars and reduce waiting time and fuel economy. Moreover, VANETs permit vehicles to exchange vital information such as providing accident warnings or notifying dangerous road conditions, which enhances safety on the road and helps prevent crashes. These novel technologies serve the broader objectives of smart city projects by improving mobility, decreasing greenhouse gas emissions, and increasing life quality for people [21].

3.1.2 Data-Driven Decision Making

AI-based VANETs also provide support in decision-making when it comes to deciding on urban development projects. Planners can access the data obtained from a VANET enabled vehicle to evaluate traffic movements, road occupancy, and plan development projects. For example, AI-assisted predictive models can identify periods of maximum traffic and recommend actions like taking specific alternative routes or increasing the number of scheduled public transport vehicles. These capabilities are essential in decongestion efforts and efficient service planning in urban areas with high population density [22].

3.2 Green Infrastructure and Eco-Friendly Designs

3.2.1 Urban Green Spaces and Parks

Due to their numerous beneficial impacts on health, society, and the environment, urban parks and green areas are essential components of green infrastructure. Acting as urban lungs, these regions boost biodiversity, improve air quality and lessen the consequences of urban heat islands. Parks and green areas not only provide leisure options but also encourage physical exercise and improve mental health. Green spaces are incorporated into city designs via efficient urban planning, ensuring accessibility and connectivity [22].

3.2.2 Sustainable Water Management

Improving water quality, minimizing flood risks, and preserving water resources are the goals of sustainable water management strategies. Some of the techniques include rainwater harvesting, permeable surfaces, and constructed wetlands. By capturing and storing rainwater for non-drinkable applications, rainwater harvesting systems lessen the pressure on city water resources. Permeable surfaces enable rainwater to infiltrate, decreasing runoff and restoring groundwater levels. Constructed wetlands naturally filter rainwater to improve its quality prior to its return to water bodies.

3.2.3 Green Roofs and Vertical Gardens

Creative methods for incorporating greenery into city landscapes consist of vertical gardens and green roofs. Green roofs adorned with plants manage stormwater runoff, reduce energy expenses, and provide insulation. Living walls, or vertical gardens, enhance air quality, provide insulation for structures, and beautify urban environments. Incorporating these elements into both new buildings and renovation projects can enhance urban greening and sustainability [32].

3.3 Mixed-Use Developments and Compact Urban Form

3.3.1 Transit-Oriented Development (Tod)

Transit-oriented development, or TOD, aims to build high-density, mixed-use communities around public transportation hubs. TOD goals are to lessen dependence on automobiles, alleviate congestion, and encourage sustainable urban development.

3.3.2 Urban Density and Land Use Efficiency

Maximizing the number of individuals and activities within a confined area is referred to as urban density and efficient land utilization. In addition to curbing urban sprawl and conserving natural environments, high-density developments also reduce the necessity for extensive infrastructure. Efficient land use management necessitates zoning regulations that promote infill development, mixed-use buildings, and the repurposing of empty spaces. These approaches reduce travel times, encourage sustainable development, and enhance the vibrancy of urban areas [33] (Fig. 1).

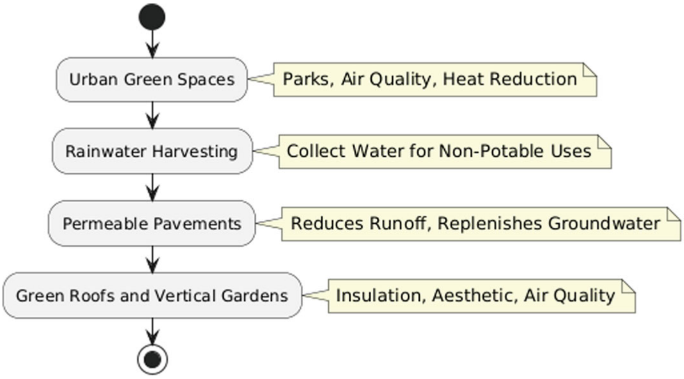
Urban Green Spaces
Parks, Air Quality, Heat Reduction
Rainwater Harvesting
Collect Water for Non-Potable Uses
Permeable Pavements
Reduces Runoff, Replenishes Groundwater
Green Roofs and Vertical Gardens
Insulation, Aesthetic, Air Quality

Fig. 1 Green infrastructure and eco-friendly designs

3.4 Participatory Planning and Community Engagement

Collaborating with stakeholders is interacting with these people or groups to get their feedback on the project. They might take part by sharing knowledge, skills, resources, and criticism, among other things. It might mean working together to accomplish the project's short-term goals or longer-termones.

Participatory workshops gather participants to solicit their thoughts or try to come up with creative, collaborative solutions to issues. Although these workshops are used in a wide range of settings, design research and participatory action research are the two most common uses for them [34] (Fig. 2).

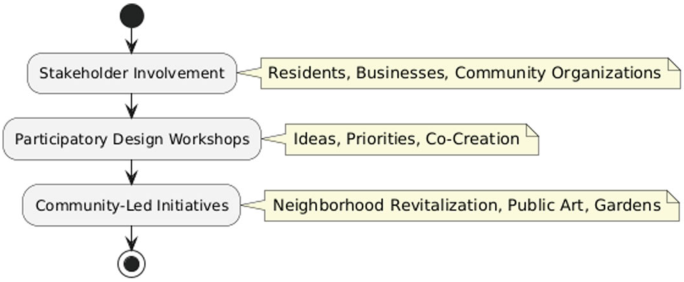
Stakeholder Involvement
Residents, Businesses, Community Organizations
Participatory Design Workshops
Ideas, Priorities, Co-Creation
Community-Led Initiatives
Neighborhood Revitalization, Public Art, Gardens

Fig. 2 Participatory planning and community engagement

4 International Policies and Agreements

4.1 United Nations Sustainable Development Goals (SDGS)

AI based VANETs actively contribute towards Sustainable Development Goal 11 by targeting urban problems like road congestion and pollution. The use of algorithms and real-time communication allows for the implementation of efficient VANETs which lead to better transportation systems. By reducing idle times and traffic congestion, greenhouse gas emissions are lowered, which is a step towards achieving global sustainability objectives. Moreover, the enhancement of transportation equity through VANETs improves access to mobility for all people [35].

4.2 Paris Agreement and Climate Action

The significant Paris Agreement, which seeks to tackle climate change and its effects, was endorsed in 2015. It brings together nations to set objectives for reducing greenhouse gas emissions and to aid global efforts aimed at preventing the warming of the planet from exceeding 2 degrees Celsius. In order to lower emissions, improve climate change resilience, and advance sustainable urban development, cities are urged under the Paris Agreement to establish and execute climate action plans. This involves financing sustainable transportation methods, enhancing the energy efficiency of buildings, and transitioning to renewable energy sources [34].

5 National and Local Government Initiatives

5.1 National Urban Policies

National governments formulate national urban policies to guide the sustainable growth of cities and urban regions. These policies seek to promote equitable, sustainable, and balanced growth by establishing strategic objectives and directions for urban development. They encompass matters such as economic growth, environmental conservation, infrastructure enhancement, and accessible housing. Green building standards, public transit financing, and renewable energy incentives are just a few instances of the targeted goals and measures that national urban policies typically incorporate to encourage sustainable urban practices [36].

5.2 Local Sustainability Plans

Local governments develop sustainability plans to tackle specific opportunities and challenges related to sustainability in their areas. These plans outline specific actions and initiatives designed to promote sustainable urban development at a local level. Typically, they encompass goals and strategies related to community engagement and the protection of green areas. In order to ensure that the plans reflect the community's needs and objectives, local sustainability initiatives often involve collaboration including the local community, such as citizens, companies, and nonprofit [37].

5.3 Zoning Laws and Sustainable Urban Codes

5.3.1 Form-Based Codes

Zoning laws known as "form-based codes" place considerable emphasis on the building and physical layout of the built environment more than just land use. In an effort to develop trustworthy and high-quality urban design, these guidelines focus significantly on the connection among buildings, streets, and public areas. Codes based on form encourage walkability, mixed-use developments, and an urban environment that is scaled for humans. Through the regulation of building design and the layout of public areas, these codes foster lively, sustainable communities that emphasize pedestrian and bike facilities, public transit, and green areas [38].

5.3.2 Incentives for Green Building

Incentives for green building refer to policies and initiatives designed to encourage the construction and renovation of structures to meet heightened energy and environmental performance standards. Developers who adopt sustainable practices can take advantage of tax credits, subsidies, low-interest loans, faster permitting processes, and density bonuses, among other benefits. The objectives of green building incentives include minimizing the environmental footprint of structures, enhancing energy efficiency, and encouraging the adoption of sustainable materials and technologies. These incentives help cities achieve their sustainability goals and reduce their total carbon footprint by encouraging eco-friendly construction practices [39].

6 Challenges and Opportunities

Urban planners are confronted with environmental issues as their top priority while striving to develop resilient, sustainable cities. Alterations in climate are endangering urban regions, making resilience strategies essential to endure extreme weather and rising sea levels. The urbanization process also disturbs ecosystems, decreasing biodiversity and natural resilience. Socioeconomic issues complicate planning as vulnerable individuals confront rising housing expenses, restricted access to services, and income inequality. Addressing these issues requires creative solutions and inclusive policies. Public–private partnerships, grassroots initiatives, and community participation, however, offer opportunities for equitable urban growth and sustainable development. Cross-sector collaboration makes cities more adaptable, inclusive, and resilient [40].

7 Conclusion

This chapter emphasizes the game-changing capabilities of AI-enabled VANETs with relation to smart city initiative. Implementation of VANETs within city transit infrastructures can offer great improvements in mobility, sustainability, and safety within the urban environment. Networks powered by AI help cities deal with critical problems like congestion and pollution in real-time, which help in the sustainable development of cities.

To tackle the growing issues related to the environment and development, cities will need to embrace technologies such as VANETs that foster resilience, flexibility, and inclusivity. These advanced networks serve as a paradigm for how contemporary technology may improve the quality of life for present and future residents and promote urban sustainability.

References

1. Carmona, M.: Public Places Urban Spaces: The Dimensions of Urban Design. Routledge (2021)
2. Groumpos, P.P.: A critical historical and scientific overview of all industrial revolutions. IFAC-PapersOnLine **54**(13), 464–471 (2021)
3. Evans, J., et al.: Smart and sustainable cities? Pipedreams, practicalities and possibilities. Local Environ. **24**(7), 557–564 (2019)
4. Strumiłło, K.: Sustainable city-green walls and roofs as ecological solution. In: IOP Conference Series: Materials Science and Engineering, p. 22110. IOP Publishing (2021)
5. Hasibuan, H.S., Mulyani, M.: Transit-oriented development: towards achieving sustainable transport and urban development in Jakarta metropolitan, Indonesia. Sustainability **14**(9), 5244 (2022)
6. Wilson, A., Tewdwr-Jones, M., Comber, R.: Urban planning, public participation and digital technology: App development as a method of generating citizen involvement in local planning processes. Environ. Plan. B Urban Anal. City Sci. **46**(2), 286–302 (2019)

7. Cappai, F., Forgues, D., Glaus, M.: A methodological approach for evaluating brownfield redevelopment projects. Urban Sci. **3**(2), 45 (2019)
8. Talen, E.: The socio-economic context of form-based codes. Landsc. Urban Plan. **214**, 104182 (2021)
9. Zhou, Q., Leng, G., Su, J., Ren, Y.: Comparison of urbanization and climate change impacts on urban flood volumes: importance of urban planning and drainage adaptation. Sci. Total. Environ. **658**, 24–33 (2019)
10. Faisal, A., Kamruzzaman, M., Yigitcanlar, T., Currie, G.: Understanding autonomous vehicles. J. Transp. Land Use **12**(1), 45–72 (2019)
11. Hoang, A.T., Nguyen, X.P.: Integrating renewable sources into energy system for smart city as a sagacious strategy towards clean and sustainable process. J. Clean. Prod. **305**, 127161 (2021)
12. Audu, A.-R.A., Cuzzocrea, A., Leung, C.K., MacLeod, K.A., Ohin, N.I., Pulgar-Vidal, N.C.: An intelligent predictive analytics system for transportation analytics on open data towards the development of a smart city. In: Complex, Intelligent, and Software Intensive Systems: Proceedings of the 13th International Conference on Complex, Intelligent, and Software Intensive Systems (CISIS-2019), pp. 224–236. Springer (2020)
13. Huang, H., Yao, X.A., Krisp, J.M., Jiang, B.: Analytics of location-based big data for smart cities: opportunities, challenges, and future directions. Comput. Environ. Urban Syst. **90**, 101712 (2021)
14. Kontokosta, C.E.: Urban informatics in the science and practice of planning. J. Plan. Educ. Res. **41**(4), 382–395 (2021)
15. Sandoval, V., Sarmiento, J.P.: A neglected issue: informal settlements, urban development, and disaster risk reduction in Latin America and the Caribbean. Disaster Prev. Manag. An Int. J. **29**(5), 731–745 (2020)
16. Granath Hansson, A.: City strategies for affordable housing: the approaches of Berlin, Hamburg, Stockholm, and Gothenburg. Int. J. Hous. Policy **19**(1), 95–119 (2019)
17. Chan, A.P.C., Adabre, M.A.: Bridging the gap between sustainable housing and affordable housing: the required critical success criteria (CSC). Build. Environ. **151**, 112–125 (2019)
18. Neuman, M.: Regional design: recovering a great landscape architecture and urban planning tradition. Landsc. Urban Plan. **47**(3–4), 115–128 (2000)
19. Gazvoda, D.: Characteristics of modern landscape architecture and its education. Landsc. Urban Plan. **60**(2), 117–133 (2002)
20. Francis, M.: A case study method for landscape architecture. Landsc. J. **20**(1), 15–29 (2001)
21. Ahern, J., Cilliers, S., Niemelä, J.: The concept of ecosystem services in adaptive urban planning and design: a framework for supporting innovation. Landsc. Urban Plan. **125**, 254–259 (2014)
22. Nyseth, T., Hamdouch, A.: The transformative power of social innovation in urban planning and local development. Urban Plan. **4**(1), 1–6 (2019)
23. Davidson, F.: Planning for performance: requirements for sustainable development. Habitat Int. **20**(3), 445–462 (1996)
24. Hameed, A.A.: Smart city planning and sustainable development. IOP Conf. Ser.: Mater. Sci. Eng. 22042 (2019)
25. Sodiq, A., et al.: Towards modern sustainable cities: review of sustainability principles and trends. J. Clean. Prod. **227**, 972–1001 (2019)
26. Meagher, B.R.: Ecologizing social psychology: the physical environment as a necessary constituent of social processes. Personal. Soc. Psychol. Rev. **24**(1), 3–23 (2020)
27. Sen, S., Guchhait, S.K.: Urban green space in India: perception of cultural ecosystem services and psychology of situatedness and connectedness. Ecol. Indic. **123**, 107338 (2021)
28. Heymans, A., Breadsell, J., Morrison, G.M., Byrne, J.J., Eon, C.: Ecological urban planning and design: a systematic literature review. Sustainability **11**(13), 3723 (2019)
29. Tzaninis, Y., Mandler, T., Kaika, M., Keil, R.: Moving urban political ecology beyond the ‘urbanization of nature.’ Prog. Hum. Geogr. **45**(2), 229–252 (2021)
30. Winkel, G., Saegert, S., Evans, G.W.: An ecological perspective on theory, methods, and analysis in environmental psychology: advances and challenges. J. Environ. Psychol. **29**(3), 318–328 (2009)

31. Gülgün, B., Güney, M.A., Aktaş, E., Yazici, K.: Role of the landscape architecture in interdisciplinary planning of sustainable cities. J. Environ. Protec. Ecol. **15**(4), 1877–1880 (2014)
32. Nguyen, P.-Y., Astell-Burt, T., Rahimi-Ardabili, H., Feng, X.: Green space quality and health: a systematic review. Int. J. Environ. Res. Public Health **18**(21), 11028 (2021)
33. Koroso, N.H., Zevenbergen, J.A., Lengoiboni, M.: Urban land use efficiency in Ethiopia: an assessment of urban land use sustainability in Addis Ababa. Land Use Policy **99**, 105081 (2020)
34. Delbeke, J., Runge-Metzger, A., Slingenberg, Y., Werksman, J.: The paris agreement. In: Towards a Climate-Neutral Europe, pp. 24–45. Routledge (2019)
35. De Roo, G., Miller, D.: Compact Cities and Sustainable Urban Development: A Critical Assessment of Policies and Plans from an International Perspective. Routledge (2019)
36. Vaidya, H., Chatterji, T.: SDG 11 sustainable cities and communities: SDG 11 and the new urban agenda: Global sustainability frameworks for local action. In: Actioning the Global Goals for Local Impact: Towards Sustainability Science, Policy, Education and Practice, pp. 173–185 (2020)
37. Hickmann, T.: Locating cities and their governments in multi-level sustainability governance. Polit. Gov. **9**(1), 211–220 (2021)
38. Serkin, C.: A case for zoning. Notre Dame L. Rev. **96**, 749 (2020)
39. He, L., Chen, L.: The incentive effects of different government subsidy policies on green buildings. Renew. Sustain. Energy Rev. **135**, 110123 (2021)
40. Tonkiss, F.: City government and urban inequalities. City **24**(1–2), 286–301 (2020)

Enhancing Urban Connectivity: Design Principles and Smart Solutions for Bridges and Highways

Muhammad Ameer Hamza, Muhammad Usama, Saad Ud Din, Ubaid Ullah, Zaid Muhammad, and Muhammad Abbas

Abstract Urban bridges have a direct impact on public safety, they are crucial components of the transportation system that require extra care. These structures, in contrast to highway bridges, frequently experience faster degradation due to increased traffic volumes, which are made worse by overloaded cars. Proactive management techniques, such putting in place vehicle weight limitations (VWRs) to reduce structural concerns, are necessary to address these issues. This study highlights how crucial precise traffic load modeling is to preserving the durability and reliability of municipal bridges. By using structural health monitoring (SHM) sensors and weigh-in-motion (WIM) devices, engineers may evaluate traffic patterns in real time and adjust load models to match the real situation. The study also looks at extrinsic elements that jeopardize bridge integrity, such as soil subsidence and pressures brought on by humans. Alongside developments in smart infrastructure, such as intelligent transportation systems (ITS) and next-generation 6G connectivity, which improve traffic management and minimize wear, new materials like ultra-high-performance concrete (UHPC) are being investigated to increase durability. The results highlight how crucial adaptive techniques are to keeping urban bridges safe and operational in the face of growing demands. These tactics include dynamic load modeling, ongoing structural examination, and incorporating developing technology.

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Keywords Urban bridges · Vehicle weight limits (VWL) · Structural health monitoring (SHM) · Ultra-high-performance concrete (UHPC) · Intelligent transportation systems (ITS)

1 Introduction

Urban bridge problems typically attract more attention than highway bridge problems because they have a direct impact on public safety. When in use, urban bridges are subject to controlled humidity, temperature, and wind. The volume of traffic is the main element influencing these factors. Recent years have seen a dramatic rise in traffic volumes due to urbanization and municipal expansion. The degeneration of metropolitan bridges is accelerated by overload cars, which might potentially cause bridge failures [1–3]. A practical and effective way to address this issue is to implement a vehicle weight limit (VWL).

Nowadays, while selecting VWL for a bridge, certain codes are mostly adhered to [4]. Truck weight estimates based on axle number and wheelbase were made by AASHTO [5]. The Federal Highway Administration (FHWA) has put out a number of formulas pertaining to a bridge's span length. A deterministic analysis of bridge limit states is used in the Chinese standard to establish The car's total weight and wheel load limit [6]. Automobile pressure is one of the main factors affecting a bridge's durability and safety. Due to China's recent sharp increase in traffic volume, overweight and heavy automobiles are becoming more and more common there Both the current traffic volume and its anticipated future growth over a specific time period are taken into consideration when determining the bridge's primary variable load, or vehicle load. The vehicle load models used in highway bridge codes must be updated often to guarantee a bridge's safety. The vehicle load selected for the bridge design needs to be compatible with the traffic characteristics of the route and suitable for the amount and state of traffic on it. Accurate vehicle load models are essential for urban bridge safety because they need to replicate actual traffic patterns. In this process, structural health monitoring (SHM) systems—which have been developed over decades for civil infrastructure such as bridges—are essential. Technology known as weigh-in-motion (WIM), which is essential for bridging SHM, allows engineers to create accurate load models and examine traffic trends. These models may be divided into two groups: fatigue load models, which measure long-term structural wear, and traffic load models, which analyze the immediate effects of cars on bridges [7–10]. Determining the vertex and edge sequences for multi-lane road segments presents difficulties when modeling highway networks. Datasets are pre-processed to preserve a single lane per highway stretch in order to remedy this. Methods include combining split roads using ArcGIS's Merge split Roads tool or filtering lanes (for example, retaining the first lane in numbered sequences). The network topology is then maintained by mapping each highway segment's endpoints to the closest equivalents in the dataset. Lastly, to preserve structural and spatial integrity, the road network model is updated by substituting precise vertex-edge sequences from the processed dataset for simplified segments [11].

A geological danger mostly brought on by human activity, such as underground mining and fluid extraction, is land subsidence (e.g., water or oil), and construction projects, poses significant risks to urban infrastructure. Uneven settling can lead to ground cracks, damaging buildings, dams, overpasses, and underground pipelines. For critical infrastructure like overpasses, deformation from subsidence may compromise structural safety, highlighting the need for proactive monitoring and mitigation strategies. Land subsidence can result in a variety of geological disasters, such as subterranean pipeline damage, housing cracking, and foundation sinking. Ground fissures caused by uneven land subsidence can cause damage to buildings, dams, overpasses, and other urban infrastructure. Since overpasses are an essential piece of transportation infrastructure, their distortion might be extremely dangerous. The highway overpass may flex unevenly and sustain partial bridge damage due to uneven soil subsidence. Dewatering and tunneling during metro station construction can also cause settling of the foundation of overpass piles [12–14]. Because they are expensive to build and there aren't many other options, bridges are essential components of the system of public transportation. Disasters of all kinds have the potential to compromise network functionality and crossing safety. Bridges serve as obstructions for nearby highways, therefore any disturbance in their functioning might affect communities' access and connections, make it more difficult to prepare for emergencies and evacuate, and negatively impact businesses and economies. Often, a bridge failure causes a critical connection to go down. Bridges are likely to be used by a large number of people, have little redundancy, and cost a lot to maintain, especially if they are a component of major transportation networks (like highways). The total operation of the road network may thus be impacted by bridge failure or shutdown, and the consequences of the failure need to be considered from a systemic perspective. At the confluence of fluid dynamics, hydrology, transport modeling and structural analysis, assessing the systemic impact is a difficult and interdisciplinary undertaking [15].

2 Literature Survey

The impacts of geometric factors on the workload of car and bus drivers were examined, and it was shown that sight distance (SD) and shoulder width (SW) had the greatest effects on the workload of vehicle drivers. Age, experience, and occupation were found to have little bearing on driver characteristics, Geometric geometry has a greater effect on drivers of cars than on drivers of buses. This conclusion, however, ignores environmental variations like weather and illumination, which may potentially impact geometry effect and driving effort [16]. the creation and deployment of a multifaceted, packaged waste management system for New York City that makes use of road, rail, and marine transportation to effectively manage household garbage while minimizing ecological impacts. The system's dependence on tide timings and sea transit creates operating delays and complications, particularly during inclement weather, even though it significantly decreases vehicle miles and environmental costs. Through creative policy and contract designs, the system combines maritime transfer stations, optimizes operations, reduces truck consumption, improves resource efficiency, and solves long-term waste management reliability. These components may restrict the system's adaptability and effectiveness, particularly in the event of unexpected outages or higher waste quantities [17].

The resistance of urban bridge networks, with a focus on the integration of cutting-edge technology like artificial intelligence to improve bridge network resilience, performance evaluation under various catastrophe scenarios, and structural health monitoring. Although there is no common standard for choosing functional indicators and resilience evaluation techniques, and its main focus is on how resilient bridge networks are to catastrophic loads. This underscores the requirement to conduct more thorough, data-based studies to fill in holes in resistance evaluation under different disaster loads and throughout the structure's life cycle. Durability models are consistently compared and used to different bridge networks and disaster situations may be hampered by the lack of a uniform framework [18]. Nonlinear dynamic analysis and ground movements that reflect two seismic hazard levels, the effects of hydrodynamics on the seismic reactions of liquefied and scour-prone coastal highway bridges were investigated. Although it only applies to a normal coastal highway bridge, the study finds that scour transfers Seismic harm occurs in cohesionless soils from the column to the pile foundation, accounting for scour depths between 0 and 6 m. Particularly at low seismic design levels, hydrodynamic factors significantly affect pile curvature but have little influence on bearing and column deformation. This scope restricts the findings' potential application to various bridge designs, soil profiles, or difficult circumstances like breaking waves, which might drastically change the outcome [19] (Table 1).

3 Design Principles of Urban Bridges and Highways

Coastal highway bridges subjected to liquefaction and scour were studied for their seismic responses to hydrodynamic effects via earth motions that represent two seismic danger levels and nonlinear analysis of dynamics. The book chapter concludes that scour transmits seismic damage from the column to the pile foundation, despite the fact that it only examines a typical coastal highway bridge on cohesionless soils with scour depths ranging from 0 to 6 m. Particularly at low seismic design levels, hydrodynamic factors significantly affect pile curvature but have little influence on bearing and column deformation. This scope restricts the findings' potential application to different soil profiles, bridge designs, or challenging conditions like breaking waves, which might significantly alter the results.

Table 1 Summary of techniques and limitations in bridge building and inspection

Ref.	Technique used	Description	Limitations
[20]	Spearman's rank correlation coefficient	A pedestrian bridge in Trabzon, Turkey: its usage, practicality, safety, and design, emphasizing the necessity for an updated design to satisfy safety and aesthetic standards	Cultural variations' effects on pedestrian bridge use, which may affect design choices
[21]	Vibration monitoring of truss systems	New design techniques and technologies to boost bridge building and inspection, with an emphasis on techniques like unmanned aerial vehicles (UAVs) and autonomous bridge building (ABC) to increase safety and efficiency	That owing to technological difficulties and legal limitations, UAVs cannot yet completely substitute human inspection for specific bridge components
[22]	Machine learning models	Using machine learning algorithms to forecast concrete's coefficient of thermal expansion and other characteristics	Lack of empirical support for ML models under diverse environmental conditions

3.1 Foundations of Urban Bridge and Highway Design

Bridges have limited plane and elevation design because of the scarcity of urban land. Because every place has its own history and culture, bridges are designed differently. Consequently, it is difficult to rebuild a bridge. If a bridge blends in with its surroundings, it is deemed attractive and lovely [23].

Micro piles have been a popular choice for bridge foundations in recent years. Micropiles reduce soil settling and manage stress concentrations such as punching shear. Furthermore, micro piles save building expenses in addition to saving time. Micropiles do have certain drawbacks, too, such bowing in weak soil layers and corrosion in dangerous settings [24] (Fig. 1).

3.2 Structural Considerations in Urban Bridge Design

Bridge inspection by hand is highly costly and time-consuming. Deploying several sensors and gathering data is an other solution. We refer to this strategy as Structural Health Monitoring (SHM). Numerous problems, including quantification, localization, and structural damage detection, are addressed by SHM. Design verification and condition-based maintenance choices are made using this data [25].

In Sherbrooke, Quebec, Canada, the first pedestrian bridge made of ultra-high-performance concrete (UHPC) was built. This marked the beginning of the use of UHPC in bridge building. The usage of UHPC improved the structure's longevity and decreased maintenance costs. In summary, this footbridge made it possible to use UHPC to bridge engineering [26].

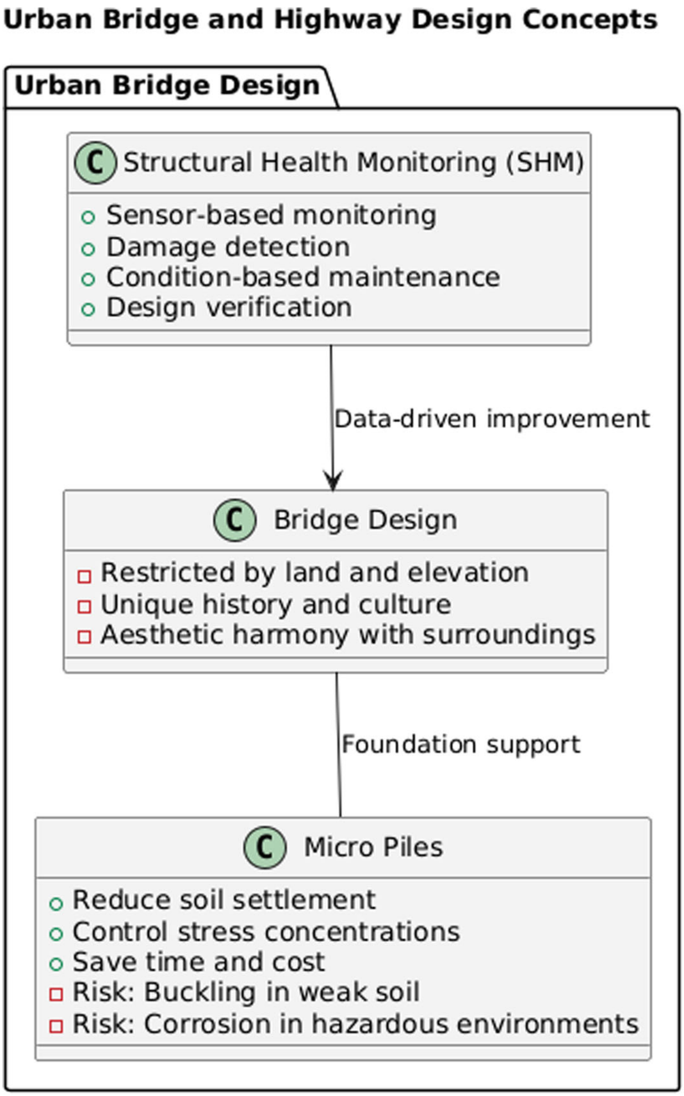
Urban Bridge and Highway Design Concepts
Urban Bridge Design
C Structural Health Monitoring (SHM)
○ Sensor-based monitoring
○ Damage detection
○ Condition-based maintenance
○ Design verification
Data-driven improvement
C Bridge Design
□ Restricted by land and elevation
□ Unique history and culture
□ Aesthetic harmony with surroundings
Foundation support
C Micro Piles
○ Reduce soil settlement
○ Control stress concentrations
○ Save time and cost
□ Risk: Buckling in weak soil
□ Risk: Corrosion in hazardous environments

Fig. 1 Key concepts in urban bridge and highway design

3.3 Traffic Flow Optimization on Urban Highways

Traffic control is crucial to sustainability and efficiency in big cities. Regression analysis is used in this study to examine traffic flow. Additionally, the study examines traffic statistics using the deep learning technology. In order to maximize urban mobility, these mathematical models are essential [27].

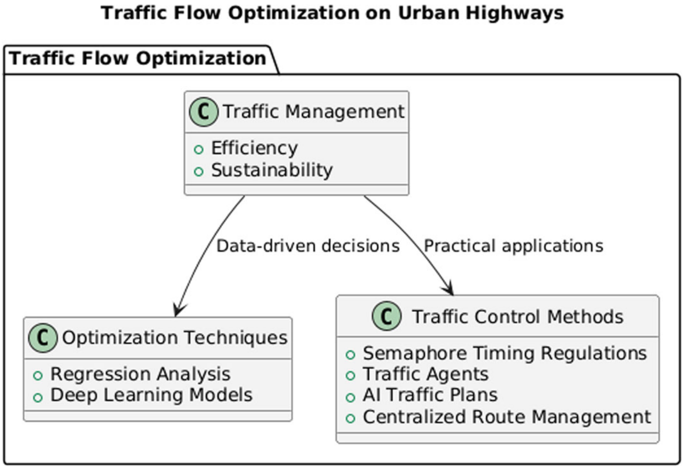
Traffic Flow Optimization on Urban Highways
Traffic Flow Optimization
Traffic Management
Efficiency
Sustainability
Data-driven decisions
Practical applications
Optimization Techniques
Regression Analysis
Deep Learning Models
Traffic Control Methods
Semaphore Timing Regulations
Traffic Agents
AI Traffic Plans
Centralized Route Management

Fig. 2 Traffic flow optimization techniques for urban highways

Semaphore timing rules are the most often used technique for controlling traffic flow. AI systems that generate traffic plans and the placement of traffic agents on the scene are other alternatives. However, centralized route management is among the greatest ways to maximize traffic flow. With this method, the traffic flow is completely under the authority of the authorities [28] (Fig. 2).

4 Challenges and Innovations in Urban Infrastructure

Urban infrastructure developments and challenges meet the changing demands of expanding cities. We shall talk about the most recent developments influencing urban transportation networks in Sect. 4.1, with an emphasis on the incorporation of innovative design principles and technology. In Sect. 4.2, common durability problems with urban bridges will be discussed, along with potential fixes to increase their longevity and dependability. Finally, in Sect. 4.3, we will look at the idea of smart roads, which are a major advancement in urban infrastructure where cutting-edge technology such as sensors and data analytics are used to improve safety and streamline traffic flow.

4.1 Evolving Trends in Urban Transportation Networks

At the UN Earth Summit in 1992, the necessity of sustainable development in urban transportation was acknowledged. Furthermore, the European Union (EU) introduced the concept of sustainable mobility in its "EU Green Paper on the Impact of Transport on the Environment." Electric cars should be powered by renewable

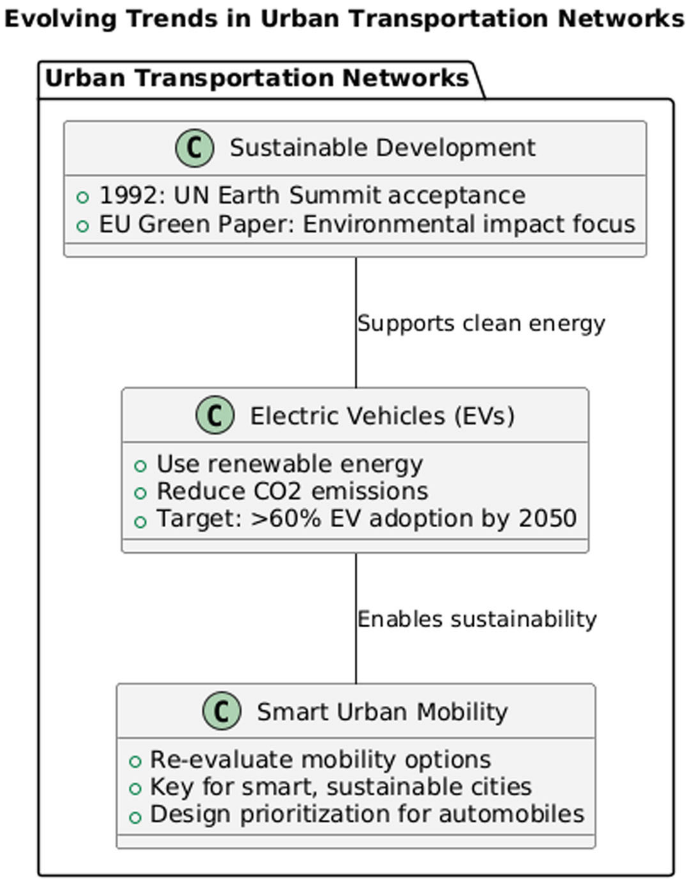
Evolving Trends in Urban Transportation Networks
Urban Transportation Networks
C Sustainable Development
1992: UN Earth Summit acceptance
EU Green Paper: Environmental impact focus
Supports clean energy
C Electric Vehicles (EVs)
Use renewable energy
Reduce CO2 emissions
Target: >60% EV adoption by 2050
Enables sustainability
C Smart Urban Mobility
Re-evaluate mobility options
Key for smart, sustainable cities
Design prioritization for automobiles

Fig. 3 Sustainable development and urban transportation trends

energy sources to enhance air quality. By 2050, 60 billion tons of CO_2 emissions might be avoided if more than 60% of automobiles are powered by electricity [29].

In order to realize the concepts of smart cities, smart urban transportation is essential. This is because more attention is paid to metropolitan areas that are built for automotive use. Therefore, it’s critical to reconsider various modes of transportation in order to make cities smarter and more sustainable [30] (Fig. 3).

4.2 Addressing Urban Bridge Durability Issues

One cutting-edge method for bridge engineering (BE) is ultra-high-performance concrete (UHPC). Because of its greater durability, UHPC is ideal for use in deep foundations for bridges. The load testing indicates that UHPC can support more

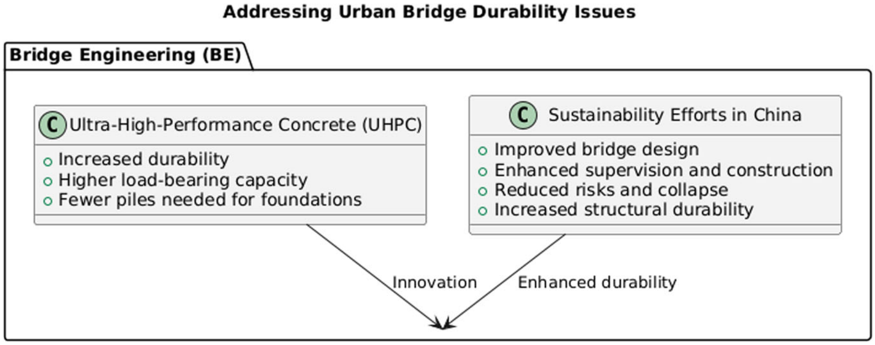
Addressing Urban Bridge Durability Issues
Bridge Engineering (BE)
C Ultra-High-Performance Concrete (UHPC)
Increased durability
Higher load-bearing capacity
Fewer piles needed for foundations
C Sustainability Efforts in China
Improved bridge design
Enhanced supervision and construction
Reduced risks and collapse
Increased structural durability
Innovation
Enhanced durability

Fig. 4 Enhancing urban bridge durability through innovative techniques

weight than steel piles, which means that fewer piles are needed for the bridge foundation [31].

China has worked hard to find solutions for Bridge Engineering's (BE) sustainability problems. A number of actions have been made to enhance the design, construction, and oversight of bridges. These steps are done to lower danger, prevent collapse, and make the construction more durable [32] (Fig. 4).

4.3 Smart Highways: Integrating Technology with Transportation

For transportation networks to function effectively, information technology utilization must be increased. Intelligent transportation systems, often known as smart transportation, integrate sophisticated sensors, computers, and management strategies to improve traffic flow and safety. Four key concepts—safety, integration, sustainability, and responsiveness—are given top priority when implementing developing technology in transportation networks [33].

Information technologies like cloud computing and the Internet of Things are essential to intelligent transportation's effectiveness. Intelligent highway transportation systems employ 6G connection to enable inadequate vehicle-to-vehicle communication in order to obtain real-time data. As a result, driving decisions are correct [34] (Fig. 5).

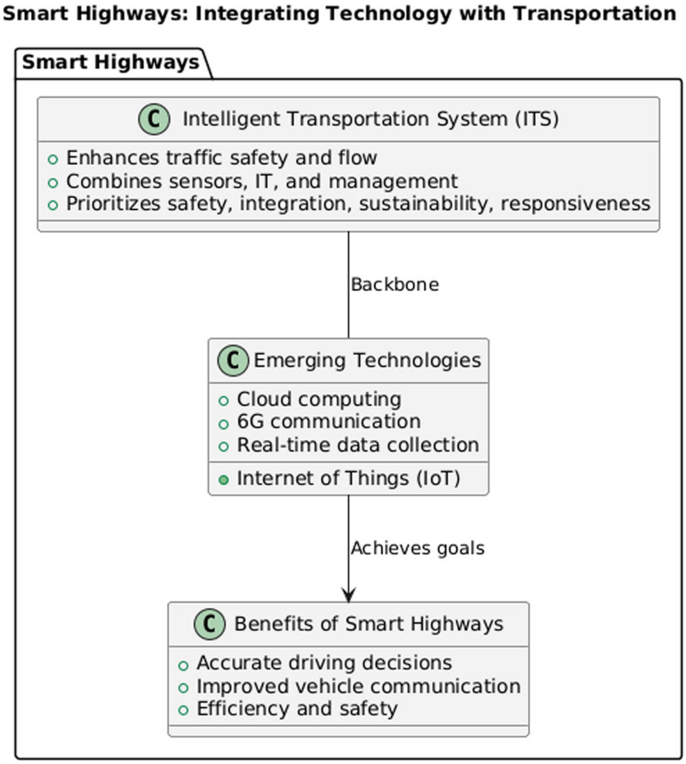
Smart Highways: Integrating Technology with Transportation
Smart Highways
C Intelligent Transportation System (ITS)
Enhances traffic safety and flow
Combines sensors, IT, and management
Prioritizes safety, integration, sustainability, responsiveness
Backbone
C Emerging Technologies
Cloud computing
6G communication
Real-time data collection
Internet of Things (IoT)
Achieves goals
C Benefits of Smart Highways
Accurate driving decisions
Improved vehicle communication
Efficiency and safety

Fig. 5 Integration of technology in smart highway

5 Conclusion

Growing traffic volumes, shifting climatic conditions, and the effects of human activity such ground subsidence present growing problems for urban bridges. In order to reduce bridge degradation, vehicle weight limitations (VWL) that are based on precise traffic estimations must be implemented. Weigh-in-motion (WIM) technologies, in particular, are essential for evaluating traffic conditions and forecasting future load demands on bridges as part of structural health monitoring (SHM) systems. Furthermore, using ultra-high-performance concrete (UHPC) and incorporating cutting-edge technology like 6G connectivity and intelligent transportation systems (ITS) offer viable ways to increase the robustness and security of urban bridges. The development of data-driven methods to track, evaluate, and improve bridge performance over time is crucial as urbanization keeps increasing. Cities may guarantee the robustness of their transportation networks and avoid expensive breakdowns by fusing state-of-the-art technology with conventional engineering methods. Future urban bridge design and traffic management will be shaped by ongoing research and technology developments, which will provide safer, more sustainable infrastructure for the expanding urban population.

References

1. Sun, Z., et al.: Load-carrying capacity evaluation of girder bridge using moving vehicle. Eng. Struct. (2021)
2. Marques, F., et al.: Weigh-in-motion implementation in an old metallic railway bridge. Eng. Struct. (2016)
3. Miao, T.J., et al.: Bridge live load models from WIM data. Eng. Struct. (2002)
4. Tabatabai, H., et al.: WIM-based assessment of load effects on bridges due to various classes of heavy trucks. Eng. Struct. (2017)
5. Seo, J., et al.: Bridge rating protocol using ambient trucks through structural health monitoring system. Eng. Struct. (2013)
6. Zhang, Z., et al.: Sparse signal recovery for WIM measurements from undersampled data through compressed sensing. Measurement (2020)
7. Worden, K., Cross, E.J.: On switching response surface models, with applications to the structural health monitoring of bridges. Mech. Syst. Signal Process. **98**, 139–156 (2018)
8. Jacob, B., O'Brien, E.J.: Weigh-in-Motion: Recent Developments in Europe (2005)
9. O'Connor, A., Eichinger, E.M.:. Site-specific traffic load modelling for bridge assessment. In: Proceedings of the Institution of Civil Engineers-Bridge Engineering, Vol. 160, No. 4, pp. 185–194. Thomas Telford Ltd. (2007)
10. Li, M., Huang, T.L., Liao, J.J., Zhong, J., Zhong, J.W.: WIM-based vehicle load models for urban highway bridge. Latin Am. J. Solids Struct. **17**(05), e290 (2020)
11. Kasmalkar, I.G., Serafin, K.A., Suckale, J.: Integrating urban traffic models with coastal flood maps to quantify the resilience of traffic systems to episodic coastal flooding. MethodsX **8**, 101483 (2021)
12. Chen, S.Z., Feng, D.C., Sun, Z.: Reliability-based vehicle weight limit determination for urban bridge network subjected to stochastic traffic flow considering vehicle-bridge coupling. Eng. Struct. **247**, 113166 (2021)
13. Gao, M., Gong, H., Li, X., Chen, B., Zhou, C., Shi, M., Guo, L., Chen, Z., Ni, Z., Duan, G.: Land subsidence and ground fissures in Beijing capital international airport (BCIA): Evidence from quasi-PS InSAR analysis. Remote Sens. **11**, 1466 (2019)
14. Lyu, M., Ke, Y., Li, X., Zhu, L., Guo, L., Gong, H.: Detection of seasonal deformation of highway overpasses using the PS-InSAR technique: a case study in Beijing urban area. Remote Sens. **12**(18), 3071 (2020)
15. Pregnolato, M., Winter, A.O., Mascarenas, D., Sen, A.D., Bates, P., Motley, M.R.: Assessing flooding impact to riverine bridges: an integrated analysis. Nat. Haz. Earth Syst. Sci. Discuss. **2020**, 1–18 (2020)
16. Jacob, A., Akkara, J., Jinesh, K.J., Therattil, J.P.: Effect of non-urban two lane highway geometry on car and bus drivers–a physiological study. Transp. Res. Proced. **62**, 358–365 (2022)
17. Yahalom, S., Guan, C., Johansson, E.: An innovative intermodal solution to urban residential waste disposal in large cities: a marine highway solution to a growing environmental problem, pp. 1–13. Maritime Economics & Logistics (2020)
18. Wang, T., Liu, Y., Li, Q., Du, P., Zheng, X., Gao, Q.: State-of-the-Art review of the resilience of urban bridge networks. Sustainability **15**(2), 989 (2023)
19. Wang, X., Pang, Y., Ye, A.: Probabilistic seismic response analysis of coastal highway bridges under scour and liquefaction conditions: does the hydrodynamic effect matter? Adv. Bridge Eng. **1**, 1–15 (2020)

20. Hełdak, M., Kurt Konakoglu, S.S., Kurdoglu, B.C., Goksal, H., Przybyła, B., Kazak, J.K.: The role and importance of a footbridge suspended over a highway in the opinion of its users—Trabzon (Turkey). Land **10**(4), 340 (2021)
21. Mahamid, M., Ozevin, D., Torra-Bilal, I., Kabir, M., Mastny, S., Khudeira, S., Sauter, B.W., Zroka, D.: Structural design and inspectability of highway bridges. Pract. Period. Struct. Des. Constr. **24**(3), 06019002 (2019)
22. Banerjee, S., Vishwanath, B.S., Devendiran, D.K.: Multihazard resilience of highway bridges and bridge networks: a review. Struct. Infrastruct. Eng. **15**(12), 1694–1714 (2019)
23. Han, Z.: Aesthetics innovation and practice of urban bridge design. Struct. Eng. Int. **31**(4), 543–549 (2021). https://doi.org/10.1080/10168664.2020.1848368
24. Farhangi, V., Karakouzian, M.: Design of Bridge Foundations Using Reinforced Micropiles
25. An, Y., Chatzi, E., Sim, S.H., Laflamme, S., Blachowski, B., Ou, J.: Recent Progress and Future Trends on Damage Identification Methods for Bridge Structures. Wiley (2019). https://doi.org/10.1002/stc.2416
26. Zhou, M., Lu, W., Song, J., Lee, G.C.: Application of Ultra-High Performance Concrete in Bridge Engineering. Elsevier Ltd. (2018). https://doi.org/10.1016/j.conbuildmat.2018.08.036
27. Ulvi, H., Yerlikaya, M.A., Yildiz, K.: Urban traffic mobility optimization model: a novel mathematical approach for predictive urban traffic analysis. Appl. Sci. (Switzerland) **14**(13) (2024). https://doi.org/10.3390/app14135873
28. Zambrano-Martinez, J.L., Calafate, C.T., Soler, D., Cano, J.C., Manzoni, P.: Modeling and characterization of traffic flows in urban environments. Sensors (Switzerland) **18**(7) (2018). https://doi.org/10.3390/s18072020
29. Gao, Y., Zhu, J.: Characteristics, impacts and trends of urban transportation. Encyclopedia **2**(2), 1168–1182 (2022). https://doi.org/10.3390/encyclopedia2020078
30. Allam, Z., Sharifi, A.: Research structure and trends of smart urban mobility. Smart Cities **5**(2), 539–561 (2022). https://doi.org/10.3390/smartcities5020029
31. Abdal, S., et al.: Application of Ultra-High-Performance Concrete in Bridge Engineering: Current Status, Limitations, Challenges, and Future Prospects. MDPI (2023). https://doi.org/10.3390/buildings13010185
32. Tang, D., Huang, M.: The Sustainable Development of Bridges in China: Collapse Cause Analysis, Existing Management Dilemmas and Potential Solutions. Multidisciplinary Digital Publishing Institute (MDPI) (2024). https://doi.org/10.3390/buildings14020419
33. Oladimeji, D., Gupta, K., Kose, N.A., Gundogan, K., Ge, L., Liang, F.: Smart Transportation: An Overview of Technologies and Applications. MDPI (2023). https://doi.org/10.3390/s23083880
34. Guo, H., Huang, R., Xu, Z.: The design of intelligent highway transportation system in smart city based on the Internet of Things. Sci. Rep. **14**(1) (2024). https://doi.org/10.1038/s41598-024-79903-0

Towards Resilient V2V Communications: AI Optimized Protocols, Performance, and Reliability in Autonomous Vehicles

Manas Kumar Yogi, Atti Mangadevi, B. Kalyan Chakravarthy, and Tarra Sekhar

Abstract This chapter introduces a novel approach leveraging Artificial Intelligence (AI) within Vehicle-to-Vehicle (V2V) communication protocols. The research focuses on three key areas: intelligent resource allocation, predictive maintenance, and enhanced security. Specifically, it explores how AI-powered methods can improve channel selection, power allocation, and bandwidth utilization. This leads to more efficient routing of information within the network, effectively mitigating communication failures and ensuring system reliability while reducing downtime. Routing refers to the process of determining the best path for data to travel across a network from a source to a destination. This research addresses security threats and methods for maintaining privacy and data integrity. Optimization, a key aspect of resource allocation, aims to find the best solution among a set of possible options, maximizing desired outcomes like efficiency and minimizing undesirable factors like latency. Machine Learning (ML), a subset of AI, is employed to enable systems to learn from data without explicit programming, improving their performance on a specific task over time. The ML techniques utilized in this chapter are for predictive maintenance and intelligent resource allocation. This research work contributes to the development of seamless and connected mobility in urban transportation. Experimental results demonstrate the effectiveness of the proposed AI-driven enhancements to the V2V communication ecosystem.

Keywords V2V · AI · ML · Routing · Optimization

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1 Introduction

Vehicle-to-Vehicle (V2V) communication is a cornerstone of the emerging connected vehicle ecosystem, enabling vehicles to exchange data in real-time to improve safety and efficiency on the roads. Vehicles are capable of obtaining precious information by communicating with each other using V2V communication, such as their speed, location, braking and steering information [1]. This leads to more efficient intervehicle traffic management, thereby facilitating safer and more agile transportation networks. For example, consider a situation where a car is about to make a sudden stop due to a hazard on the road, such as an unexpected obstacle. Using V2V communication, the vehicle can transmit a message of the braking status of the vehicle following it to the vehicles behind. Such vehicles are then able to react to move immediately either by decelerating or changing their trajectories, thus preventing a rear-impact collision. This ability can be generalized to more challenging situations, e.g., intersection, where, talking to each other, the vehicles guarantee the proper, non-collusiveness turns. V2V communication that is enabled on the whole by means of monitoring the information about the environment whose operation extends beyond the range of the sensors of the individual vehicle is the basis for the realization of semi-autonomous or autonomous driving systems where sensors and cameras are not the sole sources of the perception of the environment [2]. That enables the more effective on-line decision making, in turn, improving the quality of the driving experience. In dense traffic situations, for instance, vehicles can communicate to create an organized flow, reducing congestion and enhancing road capacity. Resilience plays an important role in an autonomous vehicle (AV) network, as the AV's safety decisions lie in the continuous, real-time data exchange with the network. Without resilient communication systems, autonomous vehicles would be unable to function safely and effectively in dynamic environments. Resilience in this context refers to the ability of a vehicle's communication network to perform reliably under various conditions, even when faced with technical issues, environmental factors, or security threats [3]. By using AI to process and analyses this data in real-time, vehicles will be able to share what it is best able to tell other cars on the road. AI algorithms are able to remove unnecessary data and to share information that avoids accidents or improves traffic efficiency. Let's say a car notices an impending collision in front of it, and displays a warning. AI may guarantee that this warning is sent at the highest priority level to vehicles in vicinity, and other less urgent information, e.g. location updates or speed changes, are transmitted at a lower priority.

AI is also of utmost importance to make V2V communication adaptive to the changing road conditions. When road traffic is heavy, AI can be helpful to rank messages according to urgency. For example, when several vehicles are approaching a traffic bottleneck, AI is able to identify the most appropriate messages to send, e.g., lane changes, and will send them to the vehicles in the best possible way. AI-aided machine learning algorithms can also continuously enhance the effectiveness of V2V systems. By learning from previous experiences and pavement condition, artificial intelligence systems can adapt the communication protocol to the future ones. That is, the system can learn and be more intelligent with time by requiring less and less manual retraining or human oversight [4]. For security, anomalies in communication patterns, as, for example, strange messages, that could indicate a malicious activity, are also applied with the use of AI. Through analyzing the flow of information between cars, AI can discover whether a car is broadcasting false or harmful information, and warn the system to act, e.g., to isolate the car or to block its messages. AI also extends the decision-making function of the autonomous vehicle, by properly combining information available from V2V exchange with other information, for instance, from sensor data, traffic lights or GPS. With this integration, autonomous vehicles are not only able to "speak" to other vehicles, but also be able to take in all of the incoming data completely and arrive at safe, informed decisions holistically. V2V communications are the basis of a new generation of road safety and autonomous driving networks. Thanks to the support of robust communication systems, vehicles are able to provide continuous reliable data exchange in adverse situations. AI greatly improves these systems by focusing on the most important information, by besting communication flows, and by providing a high level of security from malicious attacks [5]. These components collectively ensure a safer, more effective and adaptive network of roads for autonomous vehicles, facilitating confident and intelligent driving on challenging road traffic.

2 Foundations of V2V Communications

2.1 State-of-Art Technologies Enabling V2V Communications

See Table 1.

2.2 Existing Standards and Regulatory Frameworks

See Fig. 1.

2.3 Challenges in V2V Communication for Autonomous Vehicles

See Table 2.

Table 1 Taxonomy of popular V2V communication technologies [6–9]

Aspect	Dedicated short range communications (DSRC)	Cellular vehicle-to-everything (C-V2X)
Technology type	IEEE 802.11p (Wi-Fi extension)	Cellular-based (LTE and 5G)
Frequency band	5.9 GHz (dedicated spectrum)	Cellular spectrum (uses both licensed and unlicensed bands)
Communication modes	Direct communication between vehicles and infrastructure	Direct Mode (device-to-device) and network mode (via cellular network)
Latency	Low latency (ideal for safety–critical applications like collision avoidance and emergency braking)	Ultra-low latency with 5G (suitable for real-time coordination and advanced applications)
Range	Short-range communication	Extended range due to cellular infrastructure
Scalability	Limited scalability (designed for localized communication)	High scalability (handles larger data volumes and wider coverage)
Deployment cost	Cost-effective due to license-free spectrum	Higher deployment cost due to reliance on cellular infrastructure and potential network upgrades
Applications	Safety–critical systems (e.g., basic safety messages, collision warnings, lane-change assistance)	Safety and advanced features (e.g., hazard alerts, cloud integration, traffic optimization, cooperative driving)
Research focus	Improving reliability in dense and interference-prone areas; integrating with other technologies	Enhancing 5G integration, multi-connectivity, security, and AI-powered traffic management
Strengths	Proven technology, low latency, cost-efficient	Scalability, long-range communication, advanced features, better integration with future technologies
Challenges	Limited range, slower adoption in some regions	High infrastructure cost, need for significant cellular network upgrades

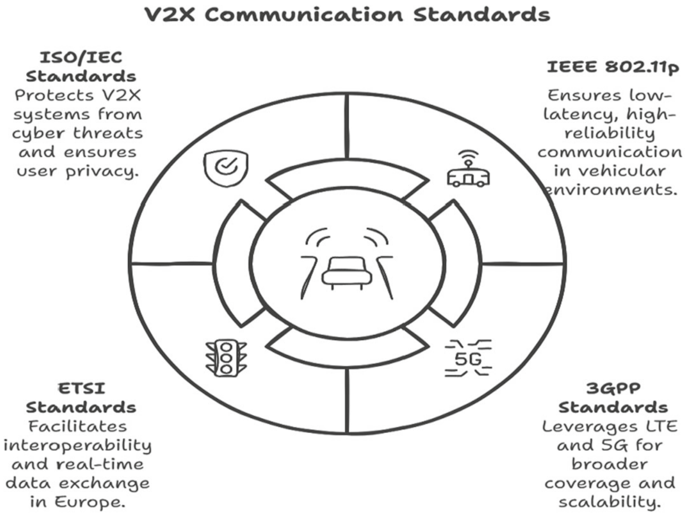
V2X Communication Standards
ISO/IEC Standards
Protects V2X systems from cyber threats and ensures user privacy.
IEEE 802.11p
Ensures low-latency, high-reliability communication in vehicular environments.
5G
ETSI Standards
Facilitates interoperability and real-time data exchange in Europe.
3GPP Standards
Leverages LTE and 5G for broader coverage and scalability.

Fig. 1 V2X communication standards

Table 2 Current practical and research challenges in V2V communications [10–14]

Challenge	Description	Examples of organizations facing issues	Proposed solutions	Research gaps identified
Latency and real-time communication	Delay in transmitting and receiving safety–critical messages, leading to potential accidents	General Motors (GM) faced latency issues in urban traffic	5G-enabled V2X communication systems	Need for ultra-low-latency networks in V2V
		NHTSA reported that V2V communication delays in dense traffic compromised safety alerts	Edge computing for faster processing	Optimizing edge processing for real-time decision-making
				Machine learning models for predictive data transmission
Interoperability and standardization	Different V2V standards (DSRC vs. C-V2X) hinder seamless communication between vehicles from different manufacturers	Toyota and Volkswagen faced interoperability issues due to different V2V standards	Adoption of unified global standards for V2V communication	Lack of universal protocols for V2V interoperability
		Qualcomm and Ericsson are working on bridging DSRC and C-V2X	Development of hybrid DSRC-C-V2X systems	Integration of multiple V2X technologies for seamless communication
Network congestion and scalability	Increased data exchange due to rising numbers of autonomous vehicles leads to bandwidth limitations and dropped messages	Tesla experienced signal drops and data loss due to congestion in dense environments	5G networks and edge computing to manage data loads	Scalability of V2V systems in high-density urban environments
			AI-driven congestion management techniques	Adaptive communication protocols for managing data load efficiently

(continued)

Table 2 (continued)

Challenge	Description	Examples of organizations facing issues	Proposed solutions	Research gaps identified
Security and privacy concerns	Vulnerabilities in V2V communication may allow malicious actors to manipulate data, causing accidents or congestion. Privacy issues arise due to vehicle tracking	Fiat Chrysler faced cybersecurity threats where hackers disrupted vehicle communication	Blockchain-based security solutions	Secure key management for V2V networks
		GDPR concerns over vehicle data tracking	End-to-end encryption for V2V messages	Privacy-preserving V2V architectures for GDPR compliance
			AI-driven anomaly detection systems	AI-driven real-time threat detection in V2V
Regulatory and legal issues	Different countries have varying spectrum allocation policies and V2V regulations, slowing down deployment	Ford and GM pushed for regulatory clarity on the 5.9 GHz spectrum in the U.S	International regulatory framework for V2V deployment	Policy harmonization for global V2V adoption
		The EU faces fragmented regulatory perspectives from different countries	Standardized legal guidelines for liability in case of V2V failures	Legal frameworks for autonomous vehicle responsibility in accidents
Environmental factors and range limitations	Weather conditions (rain, fog, snow) and physical obstacles impact signal strength and reliability	BMW faced reliability issues in adverse weather conditions during V2V pilot testing	AI-based signal enhancement	Enhancing V2V communication robustness in extreme weather
			Integration of multi-sensor fusion with V2V for redundancy	AI-powered error correction techniques for signal degradation

3 AI-Driven Optimizations in V2V Protocols

Table 3 shows various a AI methods which can be deployed for communication optimization in Vehicle-to-Vehicle (V2V) systems.

Table 3 Techniques in AI used in impactful V2V communications [15–21]

S.No.	AI technique		Advantages	Challenges	Application in V2V communications
1	Machine learning (ML)	Utilizes algorithms to learn patterns from data and improve over time	Adaptive to dynamic environments	Requires large datasets for training	Predictive maintenance, anomaly detection
2	Deep learning (DL)	A subset of ML using neural networks to model complex patterns	High accuracy and scalability	High computational cost	Traffic prediction, signal processing
3	Fuzzy logic	Mimics human reasoning by handling uncertainty and imprecise data	Robust to noise and uncertainty	Requires expert knowledge to define rules	Decision-making in uncertain traffic scenarios
4	Reinforcement learning	An ML approach where agents learn optimal policies through interactions	Effective for dynamic decision-making	Long training periods	Adaptive routing, congestion management
5	Genetic algorithms	Evolutionary algorithms that optimize solutions through selection processes	Efficient in complex optimization tasks	Computationally intensive	Resource allocation, channel selection
6	Swarm intelligence	Inspired by collective behavior in nature to solve optimization problems	Distributed and scalable	Sensitive to parameter settings	Cooperative communication, network resilience

(continued)

Table 3 (continued)

S.No.	AI technique		Advantages	Challenges	Application in V2V communications
7	Neural network (NN)	A DL architecture for pattern recognition and prediction	Handles nonlinear relationships well	Prone to overfitting and requires tuning	Signal decoding, error correction
8	Federated learning	Decentralized learning approach where models are trained across devices	Privacy-preserving, reduces data transfer	Requires coordination between nodes	Collaborative learning for V2V optimization
9	Bayesian networks	Probabilistic models for representing uncertain knowledge	Handles uncertainty and incomplete data	Requires accurate prior probabilities	Probabilistic reasoning in communication protocols
10	Hybrid approaches	Combination of various AI techniques to improve performance	Balances strengths of different methods	Integration complexity	Multi-objective optimization in V2V systems

3.1 Protocol Enhancements Through AI (e.g., Routing, Collision Avoidance, Resource Allocation)

See Fig. 2.

Proposed Model

Algorithm: AI-Based V2V Communication Optimization

Input:

V: Set of vehicles: {v1, v2, …, vn}

L: Set of communication links: {l1, l2, …, lm}

P0: Initial routing paths for each vehicle: {P0v1, P0v2, …, P0vn}

Bmax: Bandwidth limits for each link: {Bmaxl1, Bmaxl2, …, Bmaxlm}

Cth: Collision thresholds for each link: {Cthl1, Cthl2, …, Cthlm}

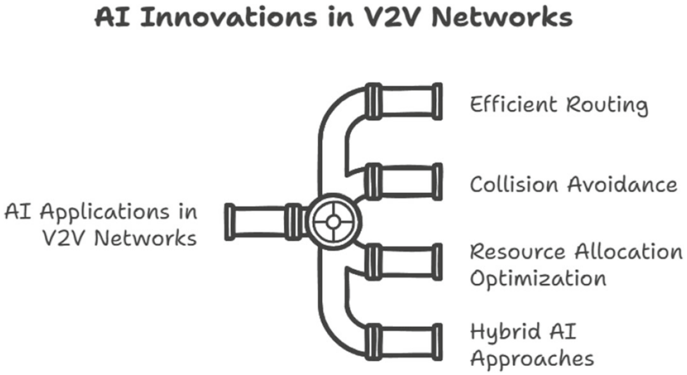
AI Innovations in V2V Networks
AI Applications in V2V Networks
Efficient Routing
Collision Avoidance
Resource Allocation Optimization
Hybrid AI Approaches

Fig. 2 Scope of AI innovations in V2V networks

Output:

P: Optimized routing paths for each vehicle: {Pv1, Pv2, …, Pvn}

C: Collision probabilities for each link: {Cl1, Cl2, …, Clm}

B: Bandwidth allocations for each link: {Bl1, Bl2, …, Blm}

Initialization:

Step 1: Initialize Routing and Bandwidth:

1. Set initial routing paths: P = P0

2. Set initial bandwidth allocations: B = B0 (e.g., equal distribution among links)

Step 2: Define Parameters:

1. Define weight coefficients: α (for routing time) and β (for collision probability)

Step 3: Initialize Data Structures:

1. Initialize data structures to store collision probabilities (C) and bandwidth allocations (B).

Main Loop (Iterate until convergence):

Step 4: Vehicle-Centric Processing:

1. For each vehicle v ∈ V:

Step 5: Data Acquisition:

i. Obtain real-time sensor data for vehicle v: {s1v, s2v, …, skv}

ii. Obtain real-time data from communication links relevant to vehicle v: {lv1, lv2, …, ljv}

Step 6: Routing Time Calculation:

i. Calculate current routing time for vehicle v: $Tvr = f(P, L, B)$ (where f is a function that calculates routing time based on path, link conditions, and bandwidth)

Step 7: Collision Probability Calculation:

i. For each link $l \in L$:

ii. Calculate collision probability: $Cl = g(P, L, B)$ (where g estimates collision probability based on paths, link conditions, and bandwidth)

Step 8: Constraint Checking and Adjustment:

i. Routing Time Constraint:

1. If $Tvr > Tvr\_max$:

2. Update routing path using reinforcement learning: $P = P + \Delta P$ (ΔP is determined by the RL algorithm)

ii. Collision Constraint:

1. For each link $l \in L$:

2. If $Cl > Cthl$:

3. Implement collision avoidance mechanisms (e.g., TDMA, FDMA, CDMA) on link l. This may involve adjusting bandwidth allocation.

iii. Bandwidth Constraint:

1. For each link $l \in L$:

2. Ensure $Bl \leq Bmaxl$. If not, adjust bandwidth allocation to respect the limit.

Step 9: Routing Optimization (Reinforcement Learning):

i. Calculate reward: $Reward = \alpha\ (1/Tvr) - \beta\ Cl$

ii. Use the reinforcement learning algorithm to update routing paths P based on the calculated reward.

Step 10: Parameter Update:

a. Update weight coefficients α and β based on feedback from the environment (e.g., gradient descent on a performance metric).

Step 11: Convergence Check:

a. Check for convergence criteria (e.g., no significant improvement in the reward function, maximum number of iterations reached). If converged, exit the loop.

Output:

Step 12: Output Results:

1. Optimized routing paths: P
2. Collision probabilities for each link: C
3. Bandwidth allocations for each link: B

End Algorithm

This version adds clear step numbers to each stage of the algorithm, making it even easier to follow and reference specific parts during implementation or discussion.

4 Experimental Results

To show the effectiveness of the proposed method, the dataset available in kaggle named Passive Vehicular Sensors Datasets available from the link https://www.kaggle.com/code/gautamrmenon/passive-vehicular-sensor-eda, is used which includes raw data available from various suitable devices like the accelerometer, gyroscope, magnetometer, GPS and camera data sampled in vehicles. A portion of the dataset is used to train the reinforcement learning agent. The agent's state would be the relevant information from the dataset (e.g., vehicle positions, link conditions, current routing paths), and its actions would be adjustments to the routing paths and communication protocols. During feature engineering new features from the raw data like congestion level on a link, traffic density around a vehicle are created which are useful to increase the reward function value for an agent.

1. Routing Time versus Training Episodes

Below graph in Fig. 3 show how the increase in the count of training episodes reduces the average routing time. This behavior of the proposed method represents a robust algorithm. To determine efficient routing paths for the vehicles this result acts a confidence builder.

2. Collision Probability versus Training Episodes

The graph in Fig. 4 denotes how the collision probability of the vehicles reduces as number of training rounds increase which in turn acts as an indicator for the reliability of the proposed method.

3. Bandwidth Utilization versus Training Episodes

The graph in Fig. 5 shows how the bandwidth utilization degree increase as number of training episodes increases. It represents how performance can be maintained while maximizing resource utilization.

4. Reward Function versus Training Episodes

The graph in Fig. 6 maps the units of reward function which is intrinsic part of reinforcement learning versus the number of training episodes. As the number

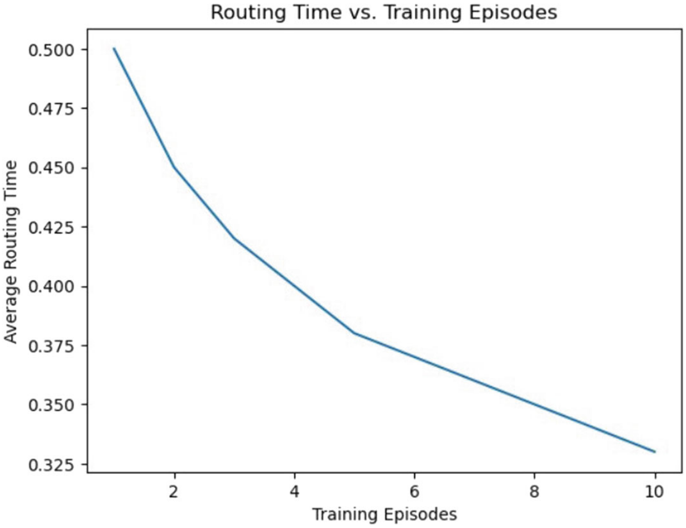

Fig. 3 Routing time versus training episodes

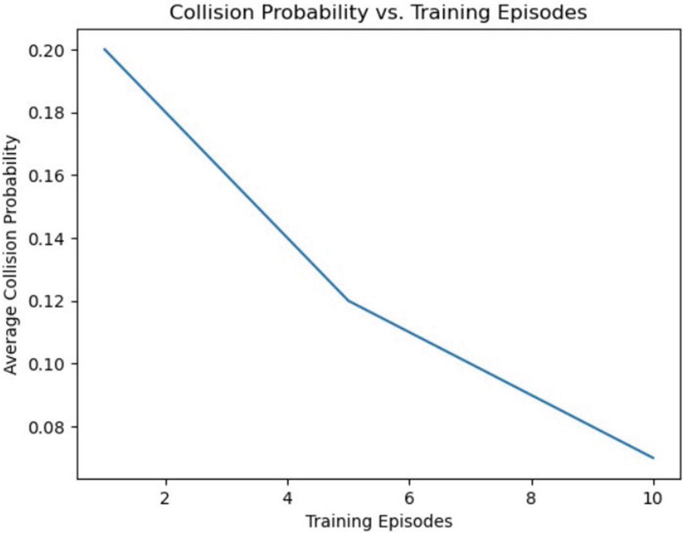

Fig. 4 Collision probability versus training episodes

of training episodes increases sharply, the degree of reward function also increases which represents the trade-off between reduced collision probability and decrease in the routing time of the vehicles. It helps in balancing the competing research objectives of the proposed mechanism.

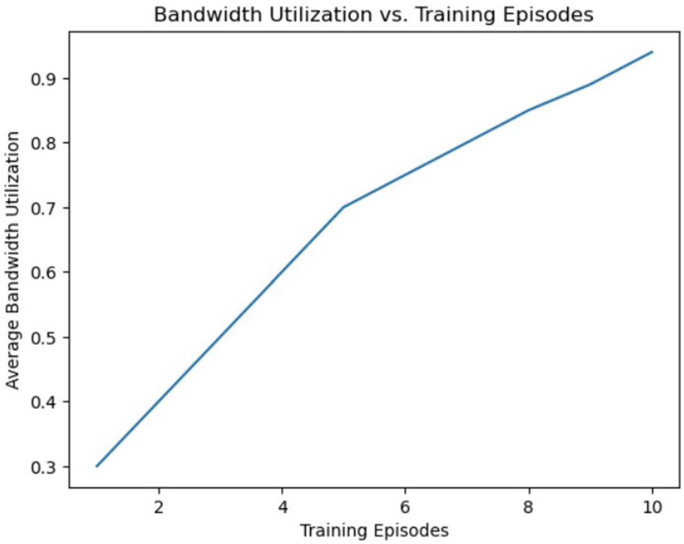

Fig. 5 Bandwidth utilization versus training episodes

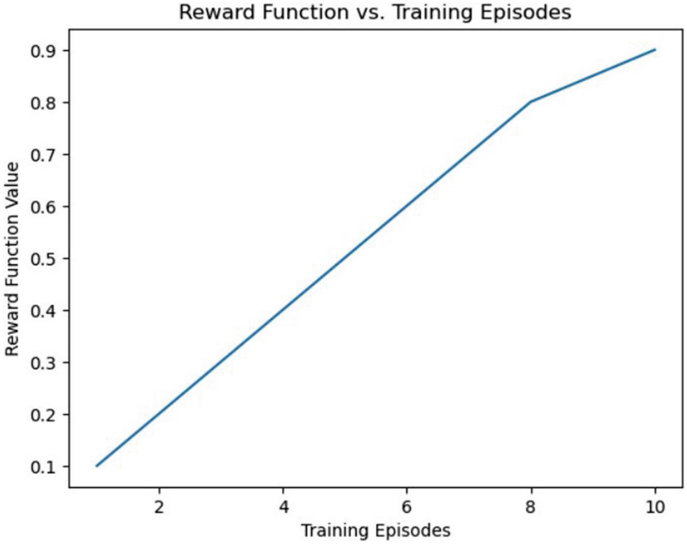

Fig. 6 Reward function versus training episodes

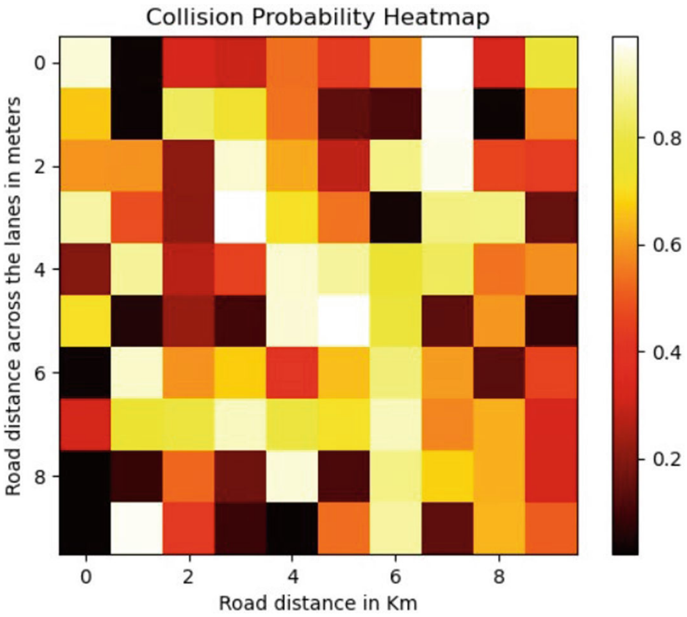

Fig. 7 Collision probability heatmap

5. Heatmap of Collision Probability

The heatmap in Fig. 7 denotes the effective visualization of spatial distribution of probability of collision in the V2V communication eco-system. This acts as helping tool to identify hotspots with high collision risks. It guides the system designers to areas where more degree of optimization is needed.

Insights:

6. Network Topology with Optimized Routes

Figure 8 shows for 20 vehicles the optimized network topology as a result of the routing decision made by the proposed algorithm. It helps in visualizing the congestion points and potential bottlenecks.

7. Comparison of Metrics with and without Optimization

The set of graphs in Fig. 9 denotes various performance metrics before and after application of the proposed method. It represents the fact that AI optimization along with reinforcement learning based mechanism proves superior when it comes to performance factors like routing time, collision probability and bandwidth utilization.

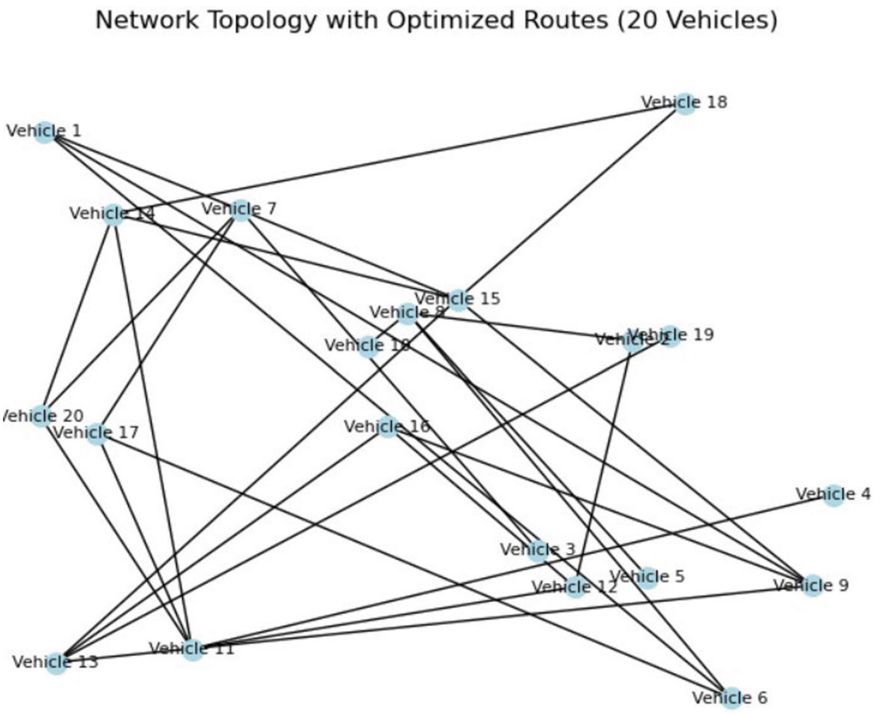
Network Topology with Optimized Routes (20 Vehicles)
Vehicle 18
Vehicle 1
Vehicle 14
Vehicle 7
Vehicle 15
Vehicle 8
Vehicle 10
Vehicle 2
Vehicle 19
Vehicle 20
Vehicle 17
Vehicle 16
Vehicle 4
Vehicle 3
Vehicle 12
Vehicle 5
Vehicle 9
Vehicle 13
Vehicle 11
Vehicle 6

Fig. 8 Network topology with optimized routes

8. Sensitivity Analysis:

Figure 10 shows the plot of sensitivity to vehicle density with respect to aspects like bandwidth usage, probability of vehicle collision and time for routing the vehicles. This graph helps the designers who are working for identifying the areas of improvement in vehicle communication optimization along with development of quality standards in the modern ecosystem of autonomous transportation.

5 Future Directions and Research Opportunities

5.1 Upcoming AI Technologies for V2V Optimization

See Table 4.

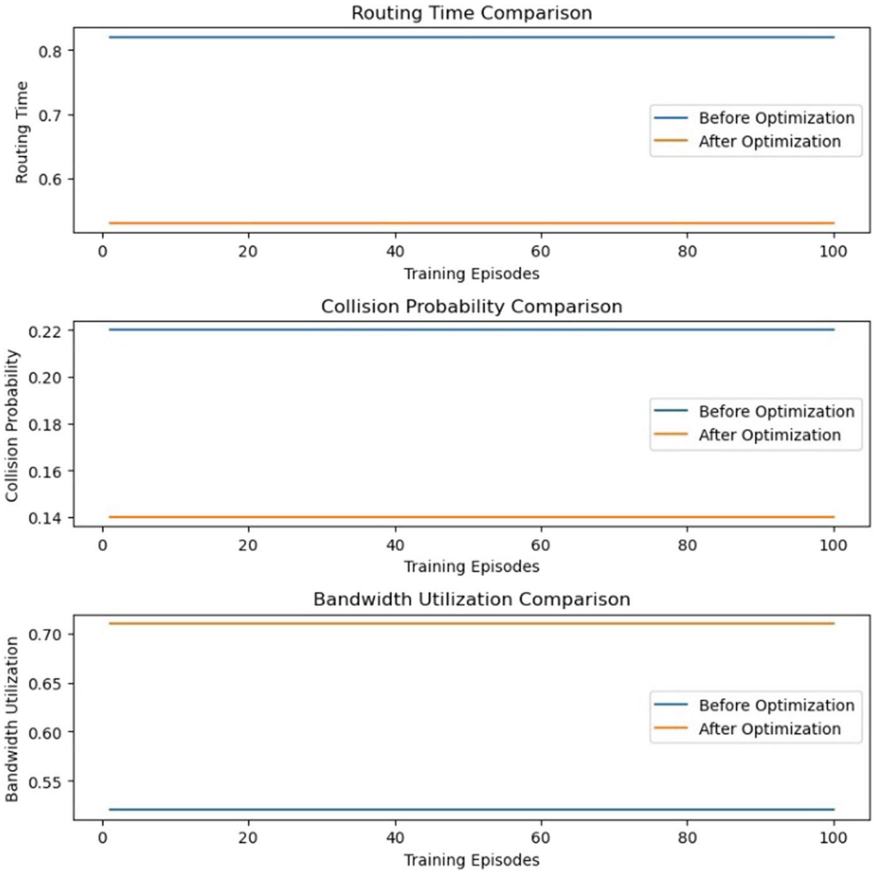

Fig. 9 Comparison of various metrics in V2V communications with and without optimization

5.2 *Long-Term Vision for Resilient Autonomous Vehicle Networks*

In below few novel aspects in this future regard are discussed [28–32]:

1. AI-Powered Predictive Maintenance:

Proactive System Health Monitoring: AI algorithms will continuously analyze vehicle sensor data, communication logs, and driving patterns to predict potential failures in components like sensors, actuators, and communication modules.

Predictive Maintenance Scheduling: This information will be used to schedule proactive maintenance, minimizing downtime and ensuring optimal vehicle performance.

Fault Diagnosis and Isolation: AI can pinpoint the root cause of failures more accurately, enabling faster and more efficient repairs.

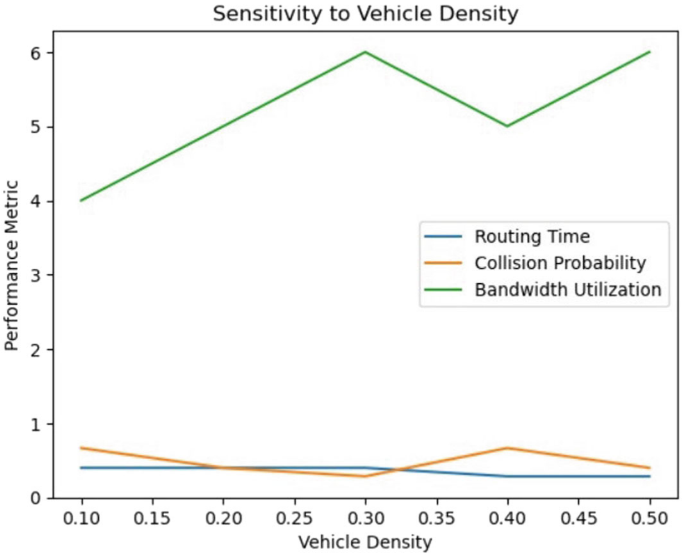

Fig. 10 Sensitivity to vehicle density

Table 4 Emerging future directions in V2V eco-system [22–27]

Nascent V2V technology	Potential	Application areas
Federated learning	Improved privacy, decentralized training, reduced latency, and adaptive model development	Collaborative AI training, real-time responses, and personalized vehicle systems
Reinforcement learning	Optimal decision-making, resource allocation, and faster learning through transfer learning	Routing optimization, communication policy improvement, and multi-agent collaboration in V2V networks
Graph neural networks	Dynamic network modeling, anomaly detection, and predictive analytics	Traffic dynamics prediction, anomaly detection in communication, and optimization of V2V communication
Explainable AI (XAI)	Transparency, debugging, and regulatory compliance	Safety–critical systems, error debugging, and fulfilling compliance requirements for V2V AI applications
Edge and fog computing	Reduced latency, improved scalability, and enhanced system reliability	Real-time processing, localized decision-making, and robust operation in unstable network conditions

2. Enhanced Situational Awareness and Risk Assessment:

AI-Driven Perception: Advanced AI/ML algorithms will enhance perception capabilities, enabling vehicles to accurately detect and classify objects (pedestrians, cyclists, other vehicles) in complex and dynamic environments.

Predictive Trajectory Forecasting: AI models will predict the future trajectories of other vehicles, pedestrians, and even unpredictable events (e.g., sudden lane changes, unexpected obstacles) to anticipate and mitigate potential hazards.

Risk Assessment and Decision-Making: AI algorithms will continuously assess risk levels and make real-time decisions to ensure safe and efficient navigation, considering factors like traffic flow, weather conditions, and potential hazards.

3. Robust Communication and Network Management:

AI-Driven Network Optimization: AI algorithms will dynamically optimize communication parameters (e.g., transmission power, frequency) to minimize interference, maximize bandwidth utilization, and ensure reliable communication in dense traffic environments.

Self-Healing Networks: AI-powered systems will be able to autonomously detect and recover from communication failures, such as link disruptions or network congestion, by dynamically adjusting communication strategies and routing protocols.

Cybersecurity Enhancement: To ensure robust cyber security and trust in the whole transportation system, AI can play a pivot role in detection of malicious activities and establishment of mitigation mechanisms.

6 Conclusion

This chapter brings out the novel properties of AI which can be helpful in optimization of protocols involved in V2V communications and protocols. AI makes predictive maintenance in smart transportation efficient and the research work in this chapter proposes the same. The results show promising directions which are self-healing in nature. The proposed method increases the trust between human users and AI systems. The proposed research paves the way towards highly reliable communication systems in the era of future 6G communication systems.

References

1. Christopoulou, M., et al.: Artificial intelligence and machine learning as important enablers for V2X communications: a comprehensive survey. Veh. Commun. **39**, 100569 (2023)
2. Westin, A.: AI-based systems for autonomous vehicle communication and coordination. J. Artif. Intell. Res. Appl. **3**(1), 1–23 (2023)

3. Khalil, A., et al.: Artificial Intelligence-based intrusion detection system for V2V communication in vehicular adhoc networks. Ain Shams Eng. J. **15**(4), 102616 (2024)
4. Yusuf, S.A., Khan, A., Souissi, R.: Vehicle-to-everything (V2X) in the autonomous vehicles domain–A technical review of communication, sensor, and AI technologies for road user safety. Transp. Res. Interdiscipl. Perspect. **23**, 100980 (2024)
5. Tong, W., et al.: Artificial intelligence for vehicle-to-everything: a survey. IEEE Access **7**, 10823–10843 (2019)
6. Yang, M., et al.: A cluster-based three-dimensional channel model for vehicle-to-vehicle communications. IEEE Trans. Veh. Technol. **68**(6), 5208–5220 (2019)
7. Ai, Y., et al.: Secure vehicular communications through reconfigurable intelligent surfaces. IEEE Trans. Veh. Technol. **70**(7), 7272–7276 (2021)
8. Ko, E., Chen, K.-C.: Wireless communications meets artificial intelligence: An illustration by autonomous vehicles on Manhattan streets. In: 2018 IEEE Global Communications Conference (GLOBECOM). IEEE (2018)
9. Pandian, A.P.D.: AI and ML cybersecurity solutions for V2V communication. In: 2022 IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS). IEEE (2022)
10. Raslan, W., et al.: Smart vehicle safety: AI-driven driver assistance and V2X communications. In: 2024 International Telecommunications Conference (ITC-Egypt). IEEE (2024)
11. Yang, M., et al.: Identification of vehicle obstruction scenario based on machine learning in vehicle-to-vehicle communications. In: 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring). IEEE (2020)
12. Haldorai, A., Murugan, S, Balakrishnan, M.: AI-based effective communication in software-defined VANET: A study. In: Artificial Intelligence for Sustainable Development. Springer Nature, Cham, Switzerland, pp 271–290 (2024)
13. Nair, A.R., et al.: AI-empowered secure data communication in V2X environment with 6G network. In: IEEE INFOCOM 2022-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS). IEEE (2022)
14. Namatherdhala, B., Mazher, N., Sriram, G.K.: Uses of artificial intelligence in autonomous driving and V2X communication. Int. Res. J. Modernization Eng. Technol. Sci. **4**(7), 1932–1936 (2022)
15. Ali, E.S., et al.: Machine learning technologies for secure vehicular communication in internet of vehicles: Recent advances and applications. Secur. Commun. Netw. **2021**(1), 8868355 (2021)
16. He, R., et al.: Vehicle-to-vehicle propagation models with large vehicle obstructions. IEEE Trans. Intell. Transp. Syst. **15**(5), 2237–2248 (2014)
17. Coello, M., et al.: Enhancing QoS in urban V2V communications through AI: a machine learning approach in vehicular ad-hoc networks. In: 2024 IEEE Eighth Ecuador Technical Chapters Meeting (ETCM). IEEE (2024)
18. Wang, L.: Enhancing vehicle-to-everything (V2X) communication with AI. J. Bioinf. Artif. Intell. **2**(2), 57–69 (2022)
19. Sanghvi, J., et al.: Res6edge: An edge-ai enabled resource sharing scheme for c-v2x communications towards 6g. In: 2021 International Wireless Communications and Mobile Computing (IWCMC). IEEE (2021)
20. Patankar, P., et al.: A novel AI-based approach for the design of VANET communication protocol. In: 2024 International Conference on Innovations and Challenges in Emerging Technologies (ICICET). IEEE (2024)
21. Pan, Q., et al.: Artificial intelligence-based energy efficient communication system for intelligent reflecting surface-driven VANETs. IEEE Trans. Intell. Transp. Syst. **23**(10), 19714–19726 (2022)
22. Liu, P., et al.: Path loss modeling for vehicle-to-vehicle communication on a slope. IEEE Trans. Veh. Technol. **63**(6), 2954–2958 (2013)
23. Yang, M., et al.: V2V channel characterization and modeling for underground parking garages. China Commun. **16**(9), 93–105 (2019)

24. Rihan, M., et al.: Deep-VFog: When artificial intelligence meets fog computing in V2X. IEEE Syst. J. **15**(3), 3492–3505 (2020)
25. Andreev, D., Trifonov, R., Lazarova, M.: Challenges regarding AI integration in V2X communication. In: 2024 12th International Scientific Conference on Computer Science (COMSCI). IEEE (2024)
26. Ekatpure, R.: Artificial intelligence for enhancing vehicle-to-everything (V2X) communication in automotive engineering: Techniques, models, and real-world applications. J. Sci. Technol. **3**(3), 91–135 (2022)
27. Ren, Z., Chen, C.: Recent advances in intelligent vehicular networks and communications. Electronics **13**(15), 3096 (2024)
28. Mohiuddin, M.A., et al.: AI to V2X privacy and security issues in autonomous vehicles: Survey. In: MATEC Web of Conferences, Vol. 392. EDP Sciences (2024)
29. Zhang, R., et al.: Generative AI-enabled vehicular networks: Fundamentals, framework, and case study. IEEE Network (2024)
30. Atov, I., et al.: Data science and artificial intelligence for communications. IEEE Commun. Mag. **57**(11), 82–83 (2019)
31. Xu, Y., et al.: V2X empowered non-signalized intersection management in the AI era: Opportunities and solutions. IEEE Commun. Stand. Mag. **4**(4), 18–25 (2020)
32. Yang, M., et al.: Dynamic V2V channel measurement and modeling at street intersection scenarios. IEEE Trans. Antennas Propag. **71**(5), 4417–4432 (2023)

UAVs and Federated Learning-Enabled Digital Twins of Vehicles in Dynamic Disaster Environments

Ehzaz Mustafa, Junaid Shuja, Faisal Rehman, Muhammad Bilal, and Muhammad Sajid Riaz

Abstract A digital twin is a virtual model of a physical system designed to ensure the quality of the physical experience. One can preferably use privacy-preserving federated learning (FL) to model digital twins of vehicular networks. However, extensive communication via the terrestrial network reduces the performance of FL, particularly in high-mobility environments like the Internet of Vehicles (IoV). IoV is a network of connected vehicles that share data among vehicles and other infrastructures, such as Roadside Units (RSUs). To overcome these limitations, unmanned aerial vehicles (UAVs) provide on-demand communication resources, especially in disaster areas. For example, in flood, earthquake, fire, and landslide scenarios, UAVs can quickly restore connectivity and support real-time data processing, enhancing the responsiveness of emergency services. We provide a high-level architecture on how UAVs assist the FL and digital twinning process in a disaster scenario. Moreover, we propose a two-layer architecture for FL-based digital twins of vehicles that strengthens communications. The emerging use cases of UAV-based FL for the digital twin of vehicles are presented along with significant challenges and potential solutions.

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Keywords Federated learning · Digital Twins · Internet of Vehicles (IoV) · Unmanned Aerial Vehicles (UAVs) · Disaster

1 Introduction

The Internet of Vehicles (IoV) is a prominent technology that enables the development of several applications for intelligent transportation systems (ITS). It is a network of connected vehicles that share data with other vehicles and infrastructures such as Roadside Units (RSUs). With sound wireless communications among vehicles and the infrastructure, intelligent traffic congestion control and autonomous driving can be perceived [1]. As innovative and novel IoV applications continue to emerge, massive amounts of data will be generated and distributed among various IoV components, such as RSUs and vehicles. Variable requirements of security, scalability, and reliability characterize ITS applications. Meeting these applications requires careful design based on a digital twin. A digital twin of vehicles will enable proactive intelligent analytics and self-sustainability for ITS while modeling the cyber-physical infrastructure in real-time [2]. A digital twin-based IoV will enable multiple tasks, such as content caching, predicting traffic diversion, and lane detection. However, such a design requires computational and storage resources. In a digital twin-based IoV, edge computing in addition to optimization, machine learning, and security-related technologies effectively serves IoV with enough computational and storage resources in closer proximity with minimum latency constraints in 5G edge networks [3, 4].

Machine learning is one of the most important technologies to enable a digital twin-based IoV. One can use centralized or distributed (i.e., federated learning (FL)) learning. Centralized learning moves the device's data to the edge or cloud to train models and, therefore, can suffer from privacy leakage. To cope with this challenge, one can use FL because vehicles are reluctant to dispense their confidential data due to the risk of leakage, misuse, and other privacy concerns [5, 6]. Edge-based FL enables digital twin-enabled IoV components to train a model using local deep learning and neural network parameters, hence mitigating privacy risks. In addition, multiple digital twin-enabled IoV components such as vehicles and RSUs collaborate with the edge server to train a model. Firstly, the edge server transmits an initial training model to the digital twin-enabled IoV components. Based on this model, each digital twin-enabled IoV component computes its local updates of the global model based on its local dataset. This efficient edge-based FL builds a road map towards ITS [7].

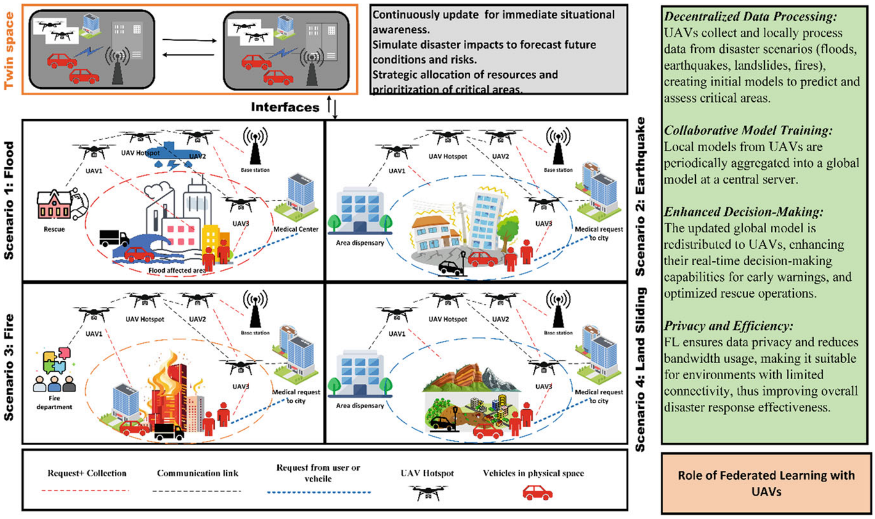
In FL, the continuous exchange of model parameters while missing seamless communication links in nodes during the FL process degrades the performance of the entire system [8]. Beyond ground data sources, aerial platforms are important due to their flexible nature. These platforms, such as unmanned aerial vehicles (UAVs), are commonly used today to provide data collection and computation offloading support for the IoV. Moreover, these UAVs provide comprehensive coverage compared to ground sources, especially in disaster areas [9].

UAVs can collect and process data from disaster scenarios and create initial models to assess critical areas such as floods, earthquakes, fires, and land sliding [10]. Consider Fig. 1, which shows how UAVs can help manage disasters. UAVs can help provide network connectivity, food, and medical services to users. In Scenario 1, the main route to the city is cut down due to floods, so UAVs can be deployed to assist users and vehicles with network connectivity, food, and medical services. Scenario 2 presents an earthquake situation in which medical and food services cannot be provided due to road conditions. Here, UAVs can work as relay networks to enable essential Internet services. In the scenario of a fire, UAVs can provide medical equipment, such as oxygen masks, to people who have difficulty breathing. Moreover, in land sliding, vehicles and users need assistance in network connectivity, food, and medical services. Despite disaster services, UAVs can assist FL and digital twining of vehicle processes to deal with disaster scenarios. For example, local UAV models are periodically aggregated into a global model on a central server, improving the accuracy and robustness of predictions across all affected areas without transferring raw data. Here, FL ensures data privacy and reduces bandwidth usage, making it suitable for environments with limited connectivity and sensitive information, thus improving overall disaster response. In addition, digital twins can continuously update vehicle sensor data for immediate situational awareness. Digital twins can simulate disaster impacts to forecast future conditions and risks. These can also aid in strategically allocating resources and prioritizing critical areas. Clustered UAVs can train digital twin models using FL, while cluster leaders (that is, central UAVs) communicate with aerial base stations and provide coverage in disaster areas [11]. The role of UAVs in the training of FL models is shown in Fig. 2. An overview of our contributions is given below.

- We present the architecture and detail of the operation of UAVs and FL in digital twins of vehicles during disaster scenarios.
- We provide multiple use cases of UAVs with FL to make the digital twin-based IoV a promising functional technology.
- We debate the issues, research challenges, and future direction of UAVs and FL-enabled digital twins to foreground IoV for novel research.

2 Uavs and Federated Learning in Digital Twins of Vehicles

Consider Fig. 2, which shows the role of UAVs in enabling FL-based digital twin of vehicles. To train digital twin models of IoV in twin space, one can preferably employ FL that will be based on training of on-device models. Then, these locally trained models are aggregated by a global aggregator in a twin space. However, deploying aggregators in a twin is challenging, especially in disaster areas and areas with insufficient terrestrial network resources. In such areas, aerial players (e.g., UAVs


Twin space
Interfaces
Scenario 1: Flood
UAV1
UAV Hotspot
UAV2
Base station
Rescue
UAV3
Medical Center
Flood affected area
Scenario 2: Earthquake
UAV1
UAV Hotspot
UAV2
Base station
Area dispensary
UAV3
Medical request to city
Scenario 3: Fire
UAV1
UAV Hotspot
UAV2
Base station
Fire department
UAV3
Medical request to city
Scenario 4: Land Sliding
UAV1
UAV Hotspot
UAV2
Base station
Area dispensary
UAV3
Medical request to city
Request+ Collection
Communication link
Request from user or vehicle
UAV Hotspot
Vehicles in physical space
Role of Federated Learning with UAVs

Continuously update for immediate situational awareness.
Simulate disaster impacts to forecast future conditions and risks.
Strategic allocation of resources and prioritization of critical areas.

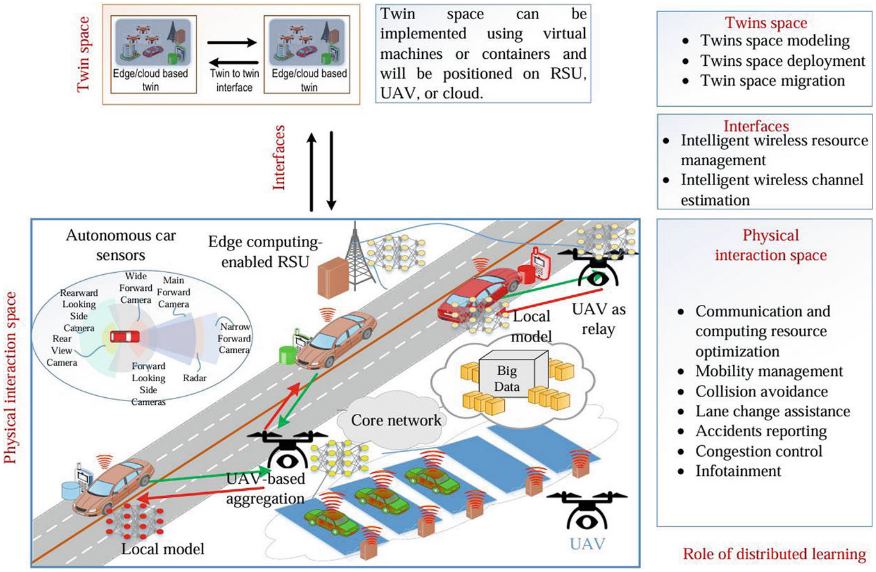
Decentralized Data Processing:
UAVs collect and locally process data from disaster scenarios (floods, earthquakes, landslides, fires), creating initial models to predict and assess critical areas.

Collaborative Model Training:
Local models from UAVs are periodically aggregated into a global model at a central server.

Enhanced Decision-Making:
The updated global model is redistributed to UAVs, enhancing their real-time decision-making capabilities for early warnings, and optimized rescue operations.

Privacy and Efficiency:
FL ensures data privacy and reduces bandwidth usage, making it suitable for environments with limited connectivity, thus improving overall disaster response effectiveness.

Fig. 1 Overview of UAVs and FL for digital twin of vehicles in disaster scenarios


Twin space
Edge/cloud based twin
Twin to twin interface
Edge/cloud based twin
Interfaces
Physical interaction space
Autonomous car sensors
Rearward Looking Side Camera
Wide Forward Camera
Main Forward Camera
Narrow Forward Camera
Rear View Camera
Forward Looking Side Cameras
Radar
Edge computing-enabled RSU
Local model
UAV as relay
Big Data
Core network
UAV-based aggregation
Local model
UAV
Role of distributed learning

Twin space can be implemented using virtual machines or containers and will be positioned on RSU, UAV, or cloud.

Twins space
- Twins space modeling
- Twins space deployment
- Twin space migration

Interfaces
- Intelligent wireless resource management
- Intelligent wireless channel estimation

Physical interaction space
- Communication and computing resource optimization
- Mobility management
- Collision avoidance
- Lane change assistance
- Accidents reporting
- Congestion control
- Infotainment

Fig. 2 Illustration of how UAVs and FL works in physical interaction space in Digital Twins of vehicles

and high-altitude platforms) can be used for the deployment of aggregators in twin space. There can be different scenarios where one can use UAVs. The first possible way can be to perform aggregation. Many local devices can train their local models and share them with a UAV where aggregation will take place. Secondly, some of the cars will have limited communication resources for communication with aggregator nodes deployed at the remote cloud. In this case, UAVs can act as a relay between the vehicle and the infrastructure (i.e., core network and cloud via RSU).

In addition to the aforementioned use cases of UAVs in enabling FL for digital twin vehicles, UAVs can be used to train a hierarchical FL model [12]. In a hierarchical FL model FL, multiple clusters train sub-global FL models in each cluster. Within each cluster, a UAV will act for performing sub-global aggregation. To train sub-global models iteratively, UAVs acting as cluster heads will share their models with the base stations where the global model is computed. Keeping in view the aforementioned uses of UAVs in training FL models for digital twin of vehicles, there is a need to resolve many challenges. These challenges are mobility management of UAVs and vehicles involved in learning, computing, and communication resource management. To resolve the issue of mobility, deep learning-enabled mobility prediction schemes can be utilized. Resource management can be addressed by computation offloading and employing optimization theory, machine learning, and game theory to make decisions about what, where, and when to offload. Next, we discuss the architecture for UAVs and FL-enabled digital twins of vehicles.

3 Architecture for UAVs and FL-enabled Digital Twins of Vehicles

The architecture of UAV and FL-enabled digital twins of vehicles consists of two layer: the physical device layer and the aggregation layer presented in Fig. 3. The physical layer contains the physical entities, such as UAVs, RSUs, edge servers, and vehicles. Our layered architecture envisions the execution of complex AI models on vehicles in a distributed fashion. On-vehicle training at the physical devices layer reduces the privacy risks of local data. These local data include vehicle identification, speed, vehicle location, and other confidential information. Vehicle sensors predict the environment including pedestrians, paths, accidents, and the speed of other vehicles. These predictions are then used in the on-vehicle training process. After the training process, the vehicles upload the trained model in gradient form to the RSUs. However, the failure of nodes and communication links of the terrestrial network during the iterative FL process degrades the performance. To this end, we propose the deployment of UAVs. These UAVs act as wireless relays and support the communication between vehicles and RSUs. Moreover, they can also be deployed to follow the corresponding vehicles for a better exchange of information. Other than that, UAVs can also be used for performing aggregation of local models of cars.

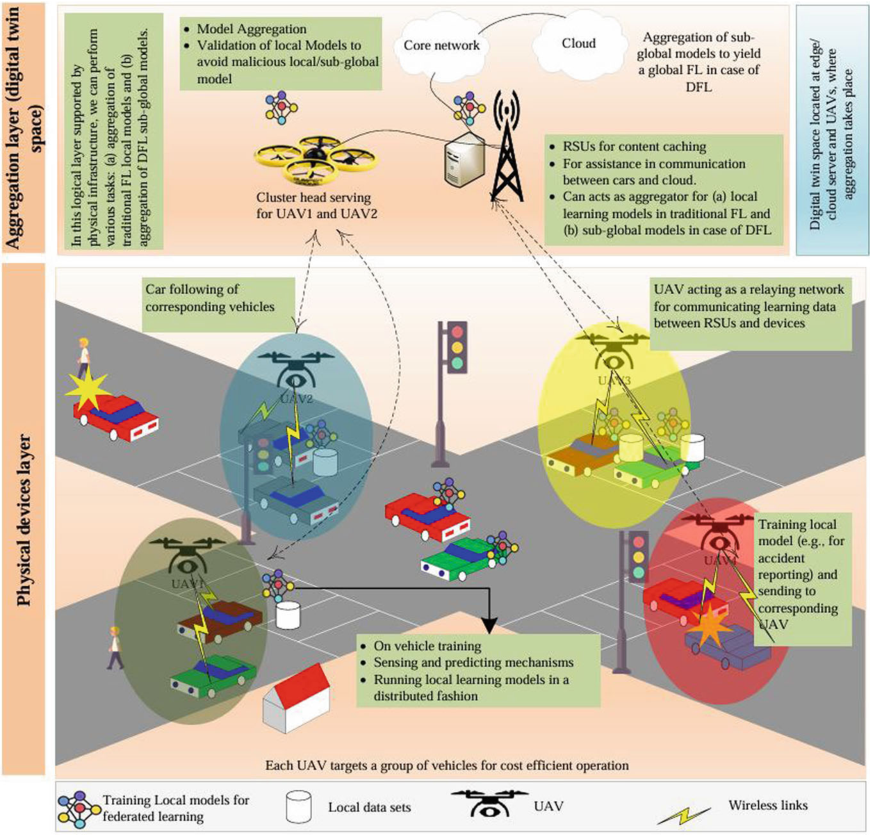

Aggregation layer (digital twin space)
In this logical layer supported by physical infrastructure, we can perform various tasks: (a) aggregation of traditional FL local models and (b) aggregation of DFL sub-global models.
• Model Aggregation
• Validation of local Models to avoid malicious local/sub-global model
Core network
Cloud
Aggregation of sub-global models to yield a global FL in case of DFL
Digital twin space located at edge/cloud server and UAVs, where aggregation takes place
Cluster head serving for UAV1 and UAV2
• RSUs for content caching
• For assistance in communication between cars and cloud.
• Can acts as aggregator for (a) local learning models in traditional FL and (b) sub-global models in case of DFL
Physical devices layer
Car following of corresponding vehicles
UAV acting as a relaying network for communicating learning data between RSUs and devices
UAV2
UAV3
UAV1
UAV4
Training local model (e.g., for accident reporting) and sending to corresponding UAV
• On vehicle training
• Sensing and predicting mechanisms
• Running local learning models in a distributed fashion
Each UAV targets a group of vehicles for cost efficient operation
Training Local models for federated learning
Local data sets
UAV
Wireless links

Fig. 3 UAVs for FL-enabled Internet of Vehicles: architecture

A single UAV may not have sufficient resources to serve the communication of learning data among vehicles and RSUs. Our architecture enables the clusters of UAVs to make the architecture more functional and effective. This enables each UAV to target a group of vehicles to communicate with physical infrastructure through aerial links and only the cluster head to communicate with the backhaul network. Through these operations, the proposed architecture effectively reduces the backhaul network traffic and provides fault-tolerant capability, which usually occurs in traditional terrestrial and aerial networks. Next, we will discuss aggregation layer deploying using UAVs.

This logical layer supported by physical infrastructure (e.g., UAVs and RSUs) performs various tasks. One can use UAVs in various ways, such as for relaying and aggregation. In the case of relaying for traditional FL, the local models communicated by UAVs (i.e., relaying) are aggregated at RSUs. These RSUs also perform other operations such as content caching and assistance in communication between vehicles and the cloud. On the other hand, cluster heads of UAVs can also be used for the aggregation of local models. Every UAV will be associated with a group of vehicles that can be used for aggregation of vehicles' local models. Meanwhile, they can also be used to validate the local models to avoid malicious local models. Second, in the case of dispersed FL, this layer enables the aggregation of sub-global models at the cluster heads and RSUs. Moreover, these RSUs forward the sub-global models using a core network to the cloud to yield a global model.

4 Use Cases

4.1 UAV-Based Aggregation

In traditional FL scenarios, edge servers are placed at a fixed location for model aggregation [13, 14]. These servers receive the local model updates, perform model aggregation, and broadcast this model to vehicles. However, the terrestrial network and infrastructure may get damaged due to several reasons (e.g., disaster) that result in difficulties in the FL process. To cope with these terrestrial limitations, UAVs may be deployed as edge servers. These can perform model aggregation and broadcast more efficiently due to their mobility. Nevertheless, a single UAV may not have enough resources to serve all the ground vehicles thus motivating the deployment of a set of UAVs. This enables the use of multiple UAVs for model aggregation and broadcasting. As depicted in Fig. 4a, a group of UAVs has a direct connection with a subset of vehicles, and their cluster heads serve as aggregation servers. One can deploy multiple groups having a subset of vehicles and cluster head (i.e., UAV) for model aggregation to boost up the FL process. These cluster heads may also communicate with each other for better aggregation and updates.

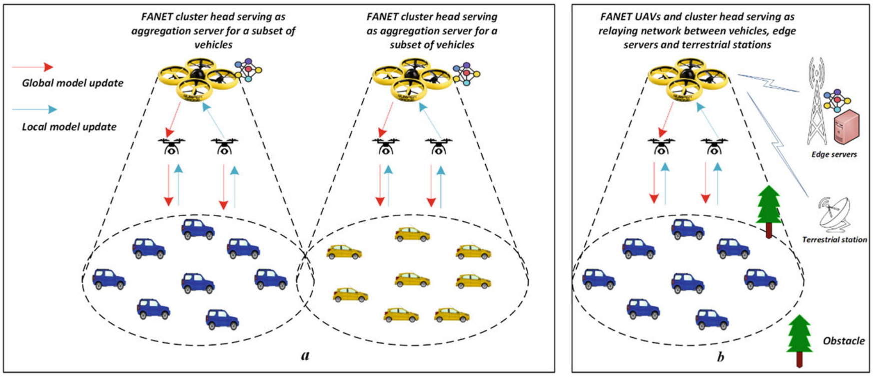

FANET cluster head serving as aggregation server for a subset of vehicles
FANET cluster head serving as aggregation server for a subset of vehicles
FANET UAVs and cluster head serving as relaying network between vehicles, edge servers and terrestrial stations
Global model update
Local model update
Edge servers
Terrestrial station
Obstacle
a
b

Fig. 4 **a** UAV-based aggregation **b** UAV-based relaying

4.2 UAV-Based Relaying

In conventional FL scenarios, vehicles transmit local model updates to nearby RSUs and edge servers. These RSUs and servers return global updates in a broadcast fashion. The transmission of local and global updates may face problems due to communication resource constraints. Low-altitude platforms may be used to communicate among vehicles and edge servers. For example, in Fig. 4b, there is no line-of-sight link between edge servers and vehicles due to obstacles. Additionally, autonomous driving cars might get out of the coverage area of the RSUs. In such cases, UAVs may be deployed as relaying networks between vehicles and RSUs or edge servers. Vehicles send local model updates to the UAVs. These UAVs migrate these updates toward edge servers through cluster heads. In return, edge servers send global model updates through UAVs to vehicles. Moreover, conventional FL for IoV may suffer from high dynamics and mobility of vehicles. It may result in an acute change in communication links. Moreover, some vehicles do not have the energy and bandwidth to communicate with the edge server directly. Through this, it is more convenient to transform the model updates between vehicles and edge servers irrespective of different obstacles and mobility patterns. Besides, cluster heads can be used to manage dynamic topologies and links.

4.3 Dispersed FL in the Sky

FL with a centralized aggregation server faces multiple challenges. For example, a single aggregation server might suffer from malfunctions. It results in degradation in the FL process. To cope with these issues, dispersed FL with UAVs may be used. In this scheme, a UAV selects a set of vehicles. After vehicle selection, each vehicle in the set computes a local model. This local model can be computed with infotainment among cars and on-board units. After the computation of the local model, these vehicles in the set send this model to the corresponding UAV. After this, the corresponding UAV computes a sub-global model. Next, the sub-global models provided from multiple sets of vehicles are aggregated at the UAV cluster head to compute the global model. This process continues for each UAV to compute sub global model for the corresponding set of vehicles, and a global model at the cluster head as depicted in Fig. 5. This figure also shows the flow of dispersed FL. Through this scheme, single server aggregation malfunctions could be tackled. Note that this application may be applied in multiple ways. For example, each cluster of UAVs may target a group of vehicles. These UAVs receive local updates and forward them to cluster heads. Then cluster heads can compute sub global model, and finally, the global model can be computed at a powerful UAV acting as head of all clusters or at edge servers. This points to two different dispersed FL schemes, centralized aggregation-enabled dispersed FL, and distributed aggregation-enabled dispersed FL.

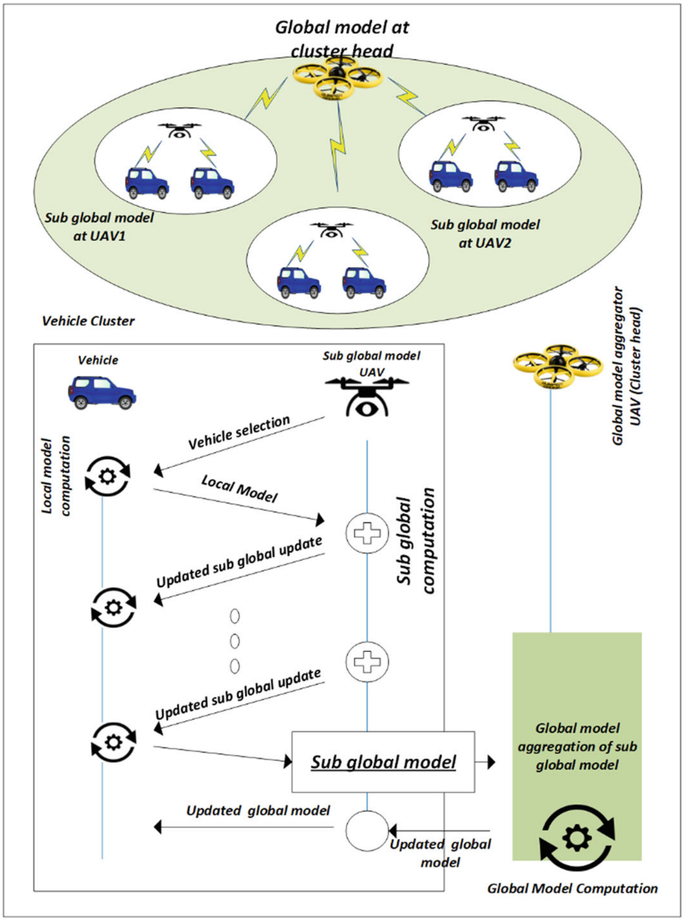

Global model at cluster head
Sub global model at UAV1
Sub global model at UAV2
Vehicle Cluster
Vehicle
Sub global model UAV
Global model aggregator UAV (Cluster head)
Vehicle selection
Local model computation
Local Model
Sub global computation
Updated sub global update
Updated sub global update
Sub global model
Global model aggregation of sub global model
Updated global model
Updated global model
Global Model Computation

Fig. 5 Dispersed FL in the sky

5 Open Challenges

5.1 Mobility and Topology Management

How do we efficiently manage the topology of UAVs for serving FL users? The predominant challenge in IoV is mobility in which vehicles are continuously moving, hence, causing difficulties in seamless communication with the edge server or central controller [15, 16]. To address this challenge, one can use UAVs to improve the FL process by becoming a relay (i.e., between vehicles and RSUs) and edge servers (i.e., for aggregation). On the other hand, UAVs also have mobility. Due to the mobility of both UAVs and vehicles involved in FL. Traditional routing algorithms might fail to fulfill the requirement of seamless communication between vehicles and UAVs.

It requires more sophisticated protocols that change the routing tables dynamically according to the movement of UAVs and vehicles [17]. Moreover, different users have different resource requirements. Therefore, dynamic placement of UAVs and cluster heads is necessary according to their resource needs. For example, a vehicle with more resource requirements should be closer to the UAV than one with mild requirements. In addition, when the number of vehicles is large enough, there is a need for multiple clusters to serve them. This will bring more challenges to mobility management such as collisions among UAVs and corresponding vehicle associations.

5.2 Energy-Efficient Deployment of UAVs for FL

How can UAVs be efficiently deployed to serve a large number of vehicular devices participating in FL? Deploying UAVs for training FL models in vehicular networks will consume a significant amount of energy. This energy is used for two purposes, such as (a) transmission of learning updates between devices/cars and UAVs and (b) keeping UAVs flying. Therefore, there is a need for efficient management/deployment of UAVs to minimize the consumption of energy. The energy-efficient deployment problem will have a combinatorial nature. To solve such problems, one can apply various algorithms: decomposition-relaxation-based schemes, deep reinforcement learning-based schemes, heuristic algorithms, and game theoretic schemes [18].

5.3 Reliability and Security

How can UAVs be deployed securely and reliably to serve FL devices in vehicular networks? To deploy UAVs for serving FL devices or vehicles, there is a need for reliable and secure communication. For reliability, one can use channel coding to make the learning process robust against channel impairments. For doing so, various channel coding schemes can be deployed. Linear block codes having low complexity can be used. However, they might not perform well in all scenarios. Coping with this, one should use convolutional codes or Turbo codes. Although Turbo codes can perform well, but at the cost of increasing in complexity of the decoder. Therefore, a tradeoff should be made while selecting channel coding schemes for communication between UAVs and vehicles for training the FL model. On the other hand, a malicious user can access the wireless FL data and alter it to prolong/stop the learning process. To tackle this, one must use effective encryption schemes (e.g., homomorphic encryption).

5.4 Interoperability

How to enable seamless interaction between UAVs and vehicles/devices to enable efficient learning of the FL global model? In the FL-based internet of vehicles, there is a variety of players, such as cloud/edge servers, vehicles, devices, and UAVs. Enabling interaction among these players for training the global FL model is a challenging task. Specifically, for seamless communication between these players, one must propose novel and general interfaces for communication. Although such general interfaces can resolve the challenge of interoperable communication, designing such interfaces is challenging and will require significant effort [19, 20].

5.5 Field Implementation and Simulation Gap

How to integrate the simulations of UAV networks and digital twins to enable an effective setup? Besides the fact of the effectiveness of FANET-enabled FL, the practical implementation is much more challenging due to several factors. For example, limited personnel resources and high cost may prevent the development of prototypes and their actual deployment. Moreover, there is a simulation gap between FL models, FANET components, and IoV. This requires the development of emulation tools that should be open to the research community.

6 Conclusion

In this work, the proposal of using digital twins, which rely on a virtual model of the physical system, was made. It is concluded that privacy-preserving federated learning (FL) would be the ideal method for modeling digital twins of vehicular networks. However, the performance of FL could be degraded by the extensive communication required in a dynamic and high-mobility environment, especially through terrestrial networks. To address this limitation, the use of unmanned aerial vehicles (UAVs) was suggested to provide on-demand communication resources, particularly in disaster areas. Moreover, the emerging use cases of UAVs and FL-enabled digital twins of vehicles were presented. A two-layer architecture for FL-based digital twins of vehicles was proposed to strengthen communication. Finally, major challenges were discussed, along with their causes and potential solutions.

References

1. Yang, S., Huang, Y., Li, L., Feng, S., Na, X., Chen, H., Khajepour, A.: How to guarantee driving safety for autonomous vehicles in a real-world environment: a perspective on self-evolution mechanisms. IEEE Intell. Transp. Syst. Mag. (2024)
2. Xiang, C., Feng, C., Xie, X., Shi, B., Lu, H., Lv, Y., Yang, M., Niu, Z.: Multi-sensor fusion and cooperative perception for autonomous driving: a review. IEEE Intell. Transp. Syst. Mag. (2023)
3. Khan, L., Mustafa, E., Shuja, J., Rehman, F., Bilal, K., Han, Z., Hong, C.: Federated learning for digital twin-based vehicular networks: architecture and challenges. IEEE Wirel. Commun. (2023)
4. Maray, M., Mustafa, E., Shuja, J.: Wireless power assisted computation offloading in mobile edge computing: a deep reinforcement learning approach. Hum.-Centric Comput. Inf. Sci. **14**, 22 (2024)
5. Musa, S., Zennaro, M., Libsie, M., Pietrosemoli, E.: Convergence of information-centric networks and edge intelligence for IoV: challenges and future directions. Future Internet **14**, 192 (2022)
6. Sharma, S., Kaushik, B.: A survey on internet of vehicles: applications, security issues & solutions. Veh. Commun. **20**, 100182 (2019)
7. McMahan, B., Moore, E., Ramage, D., Hampson, S., Arcas, B.: Communication-efficient learning of deep networks from decentralized data. In: Artificial Intelligence and Statistics, pp. 1273–1282 (2017)
8. Javed, A., Hassan, M., Shahzad, F., Ahmed, W., Singh, S., Baker, T., Gadekallu, T.: Integration of blockchain technology and federated learning in vehicular (IoT) networks: a comprehensive survey. Sensors **22**, 4394 (2022)
9. Du, Z., Wu, C., Yoshinaga, T., Yau, K., Ji, Y., Li, J.: Federated learning for vehicular internet of things: recent advances and open issues. IEEE Open J. Comp. Soc. **1**, 45–61 (2020)
10. Ng, J., Lim, W., Dai, H., Xiong, Z., Huang, J., Niyato, D., Hua, X., Leung, C., Miao, C.: Joint auction-coalition formation framework for communication-efficient federated learning in UAV-enabled internet of vehicles. IEEE Trans. Intell. Transp. Syst. **22**, 2326–2344 (2020)
11. Srivastava, A., Prakash, J.: Future FANET with application and enabling techniques: anatomization and sustainability issues. Comp. Sci. Rev. **39**, 100359 (2021)
12. Masroor, R., Naeem, M., Ejaz, W.: Efficient deployment of UAVs for disaster management: a multi-criterion optimization approach. Comput. Commun. **177**, 185–194 (2021)
13. Das, A., Halder, T., Basu, S., Sarkar, S., Basak, A., Ray, A., Chakravarty, D.: An emerging change in FANET—a status review. In: 2022 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), pp. 1–5 (2022)
14. Khan, L., Saad, W., Han, Z., Hong, C.: Dispersed federated learning: vision, taxonomy, and future directions. IEEE Wirel. Commun. **28**, 192–198 (2021)
15. Banabilah, S., Aloqaily, M., Alsayed, E., Malik, N., Jararweh, Y.: Federated learning review: fundamentals, enabling technologies, and future applications. Inf. Process. Manage. **59**, 103061 (2022)
16. Kovačić, M., Mutavdžija, M., Buntak, K.: New paradigm of sustainable urban mobility: electric and autonomous vehicles—a review and bibliometric analysis. Sustainability **14**, 9525 (2022)
17. Karam, S.N., Bilal, K., Shuja, J., Khan, L.U., Bilal, M., Khan, M.K.: Intelligent IoT- and UAV-assisted architecture for pipeline monitoring in OGI. IT Prof. **26**(3), 46–54 (2024). https://doi.org/10.1109/MITP.2023.3339448
18. Jamil, S., Fawad, M.: A comprehensive survey of digital twins and federated learning for industrial internet of things (IIoT), internet of vehicles (IoV) and internet of drones (IoD). Appl. Syst. Innov. **5**(3), 56 (2022)
19. Singh, P., et al.: GenAI-enhanced federated multi-agent DRL for digital twin-assisted IoV networks. IEEE Internet of Things J. (2025)

20. Okegbile, S.D., Gao, H., Talabi, O., Cai, J., Yi, C., Niyato, D., Shen, X.: FLeS: A federated learning-enhanced semantic communication framework for mobile AIGC-driven human digital twins. IEEE Netw. (2025)

Performance Analysis of OFDM Techniques for Short Range V2V Communication

Mohammed El Ghzaoui

Abstract The imminent arrival of autonomous vehicles on our roads is hardly in doubt, even though the timeline for their introduction and the level of their autonomy remain subjects of debate. It is clear that these vehicles will be highly connected to maximize their benefits in terms of safety and efficiency, especially since the necessary technologies (C-ITS standards) are already in place. However, this optimistic vision masks certain challenges, particularly the question of how autonomous vehicles should communicate. Closely linked to this is another issue: what communication techniques are most suitable for vehicular communication. In this chapter, the overall performance of V2V (Vehicle-to-vehicle) communication is evaluated by using an efficient modulation technique such as orthogonal frequency division multiplexing (OFDM). Indeed, OFDM is widely utilized as a modulation scheme because of its resilience, efficient use of the frequency spectrum, and ability to mitigate intersymbol interference (ISI). In the proposed work, the performance of the modulation scheme was evaluated across various channel models. Simulation parameters such as bit error rate (BER) versus signal-to-noise ratio (SNR) were plotted and analyzed in this chapter. Through a comprehensive evaluation of data rate and error performance, The findings reveal that OFDM with QAM modulation outperforms OFDM-QPSK, making it the optimal solution for V2V communication.

Keywords V2V · OFDM · BER · SNR · V2V channel

1 Introduction

Modern vehicles are increasingly equipped with radar sensors to enhance safety, improve driving comfort, and reduce road accidents [1, 2]. These sensors provide several benefits, including detecting nearby vehicles and pedestrians, identifying available parking spaces, measuring inter-vehicle distances, and warning drivers of

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potential collisions. They also support lane-changing maneuvers, contributing to overall driving safety. While LiDAR and ViLDAR systems offer advanced sensing capabilities, traditional radar sensors remain essential, particularly in challenging weather conditions such as rain or fog, where optical signal propagation is hindered. Beyond sensing, vehicles also rely on communication systems for various functions, including entertainment, real-time traffic updates, and safety alerts. Historically, radar and communication have been treated as separate entities, operating on distinct frequency bands with independent systems. The new works on this topic has increasingly focused on integrating these functionalities into a unified system known as Dual Function Radar Communication (DFRC) [3, 4]. This integration presents multiple advantages, such as reducing power consumption, lowering costs, and maximizing the efficient use of the radio frequency (RF) spectrum. These benefits are particularly significant in vehicular environments, where excessive power usage, interference, and spectrum congestion pose critical challenges, especially in densely populated urban areas. Additionally, developing cost-effective smart vehicles is crucial for the widespread adoption of intelligent transportation systems, making DFRC an essential innovation for future vehicular networks.

To effectively assess the performance of inter-vehicle communications (IVCs), it is essential to utilize suitable statistical models for fading channels in communication systems [5–7]. However, both experimental observations and theoretical studies suggest that conventional models like Rayleigh or Rician fading may not accurately capture the characteristics of Inter-Vehicular Communication (IVC) environments. The core concept of the SOS model is that the number of scatterers affecting signal propagation changes based on the space that separate the sender and receiver. Consequently, the received signal typically comprises multi-path components. Empirical studies have corroborated the validity of the SOS model through measurements conducted in diverse mobile-to-mobile communication environments. To improve system reliability in IVC scenarios, Orthogonal Frequency-Division Multiplexing (OFDM) systems have been extensively investigated in the literature [8, 9]. This is despite the fact that current vehicular communication standards, such as IEEE 802.11p and WAVE, primarily rely on single-antenna transmission. The exploration of OFDM-based solutions highlights the ongoing efforts to address the unique challenges posed by dynamic and high-mobility communication environments. By leveraging the highly dynamic nature of the V2V channel, OFDM enhances communication reliability, extends link range, increases network throughput, and mitigates multiuser interference. Given these advantages, OFDM is considered a crucial enabler for robust and efficient V2V communications [10–13].

This study utilizes a nonlinear model to explore the implementation of nonlinear modulation techniques in multipath V2V communication channels. The proposed nonlinear modulation approach encodes data by exploiting variations in channel gain within each OFDM symbol, which are affected by Doppler shifts [14]. The main objective of this research is to attain better BER performance compared to traditional linear modulation methods. Besides, the study examines channel capacity under different Doppler conditions, offering valuable insights into the effectiveness of nonlinear modulation in highly dynamic and high-mobility environments. By addressing these factors, the research aims to enhance the reliability and efficiency of data transmission in V2V communication systems. In this chapter, the overall performance of V2V communication is assessed using OFDM. Given the highly dynamic nature of V2V communication, selecting the most suitable modulation scheme is essential for ensuring reliable data transmission, minimizing errors, and optimizing bandwidth utilization. The study examines how each modulation technique performs under varying channel conditions, including multipath fading and interference, which are common in vehicular environments. The robustness of each approach is assessed in terms of its ability to maintain a stable communication link despite fluctuations in channel quality.

2 System and Channel Model

2.1 Vehicle-to-Vehicle Communication

Vehicular communications have been a research topic nearly as old as autonomous driving itself, yet both have evolved independently. The convergence of these technologies is highly desirable, as an autonomous and connected vehicle would become an intelligent agent of versatile mobility [15–17]. However, achieving this integration requires a certain level of standardization. Currently, with the vast diversity of message types and use cases, there is a growing trend toward the specialization of communication systems, as seen with technologies like eCall and geonetworking. Non-orthogonal multiple access could be a good solution for V2V communication [18, 19]. Besides, one potential solution is the emergence of near-monopolies, where a dominant platform resolves interoperability issues—a well-known “first takes all” strategy. Alternatively, our proposed approach envisions autonomous and connected vehicles as integral components of the future Internet of Things (IoT), structuring communications in a way that allows for the development of an unimaginable variety of applications. To effectively organize these communications, it is crucial to determine what information is needed, who generates it, and who the intended recipient is. While we focus here on autonomous vehicles—a field where significant progress has already been made—this analysis is quite general and can easily be applied to many other contexts.

Figure 1 depicts the V2V communication network, comprising multiple vehicles traveling either in the same route or in reverse directions on the road. The communication between vehicles is influenced by various factors, including road conditions, environmental obstacles, and surrounding infrastructure, such as buildings, tunnels, and trees, which can cause signal blockage, reflection, or scattering. These environmental factors contribute to variations in signal strength, interference levels, and overall network reliability. In fact, Rapid changes in speed and direction introduce Doppler shifts, which can distort the transmitted signal and affect data accuracy. Besides, the varying distances between vehicles also influence link

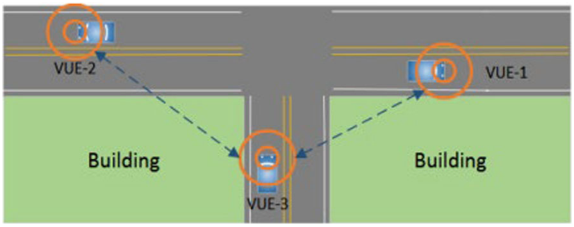


Fig. 1 V2V communication network

stability, requiring efficient channel estimation and adaptive modulation techniques to maintain seamless data exchange.

2.2 Vehicle-to-Vehicle Multipath Fading Channel

Channel modeling is a crucial field in telecommunications that involves representing the characteristics of a communication channel to optimize data transmission. It enables the simulation and prediction of signal interactions with the environment, thereby improving the reliability and quality of communication systems. By understanding channel models, researchers can design more efficient systems for a wide range of applications. Two channel model for V2V communication will be considered in this chapter.

(a) **Frequency non-selective channels**

In this subsection, the description of the received symbol is extended to fading channels. In the case of a frequency non-selective fading, the signal the receiver side is giving by:

$$r(t) = ae^{j\theta_0}s(t) + n(t) \tag{1}$$

$s(t)$ is the sent signal, a and θ_0 are respectively amplitude and phase of the Channel and $n(t)$ is the noise. So that, at the receiver side we could write:

$$r(t) = \int_{-\infty}^{\infty} h(t)s(t-\tau)\mathrm{d}\tau + n(t) \tag{2}$$

And the response in the time domain represented by

$$h(t) = ae^{j\theta_0}\delta(t) \tag{3}$$

whereas, the transfer function is given by:

$$H(f) = FT\{h(\tau)\}(f) = ae^{j\theta_0} \tag{4}$$

Which could be considered as constant over all frequencies, meaning it is non-selective in frequency.

(b) Frequency-selective fading channels

In this case, the channel will be a time-dispersive and has an response in time domain $h(\tau)$ which has a value over the interval $0 \leq \tau \leq \tau_{\max}$, by considering $\tau_{\max}$ as the maximum propagation delay of the channel. At the receiver we have

$$r(t) = \int_{0}^{\tau_{\max}} h(\tau)s(t-\tau)\mathrm{d}\tau + n(t) \tag{5}$$

In most current use cases, the signal *s(t)* has a block structure, the symbol duration must be longer than $\tau_{\max}$. At the receiver side with sampled frequency of 1/Ts, the discrete-time model representing the samples to be processed at the receiver can be described as:

$$r[i] = \sum_{m=0}^{N_C-1} h[m]s[i-m] + n[i], \quad i = 0, 1, \ldots, N_B - 1 \tag{6}$$

(c) Channel Modeling Procedure

The channel modeling procedure is the following steps:

Step 1: Find the value of $h(t)$ for different delays τ_p using the random value generation operator. Alternatively, consider a_p and θ_p as random values for different paths P to the receiver for the same transmitted impulse. In other words, determine the value of $h(t)$ for different delays τ_p.

$$h(t,\tau) = \sum_{p=1}^{P} a_p(t)\delta(\tau - \tau_p(t))e^{-j\theta_p(t)} \tag{7}$$

where a_p, τ_p et θ_p They are, respectively, the attenuation, the arrival delay, and the phase corresponding to path P.

Step 2: Calculate the received multi-path signal power P_r for a transmitted signal power P_t as a function of the delays.

Step 3: Find the multi-path parameters: the mean delay τ_{mean}, then the RMS delay τ_{rms}

Step 4: Find the coherence bandwidth B_C from the RMS delay and compare it with the bandwidth of the transmitted signal B_S to classify the channels as flat fading or frequency-selective fading.

Step 5: Find the Doppler spread f_d, then calculate the coherence time T_C.

Step 6: Compare T_C with the symbol duration T_S to classify the channel as fast fading or slow fading.

2.3 *OFDM Transceiver*

The fundamental concept/principle behind OFDM is to facilitate high-speed data transmission without relying on conventional equalization methods. Rather than transmitting symbols one after another in a sequential manner, OFDM transmits N symbols simultaneously as a block. This approach divides the available bandwidth into multiple orthogonal subcarriers, allowing for efficient and robust communication, particularly in environments prone to multipath interference and frequency-selective fading. By leveraging this parallel transmission technique, OFDM significantly enhances data throughput and reliability, making it a cornerstone of modern wireless communication systems.

2.4 *Basic Principle and Transmission Efficiency*

In the case of the multi-carrier OFDM waveform, The T_B duration is N times longer than the symbol period. This extended block duration allows for the simultaneous transmission of multiple symbols across orthogonal subcarriers, enhancing spectral efficiency and robustness against channel impairments such as multipath fading. By leveraging this approach, OFDM effectively mitigates the need for complex equalization techniques while maintaining high data rates. . For example, if $N = 128$, the symbol duration $T_B = NT_s = 128 \times 0.5\ \mu\text{s} = 64\ \mu\text{s}$, During this interval, a cyclic prefix is transmitted, ensuring that the delayed versions of the signal do not interfere with subsequent blocks. This technique preserves the orthogonality of the subcarriers and maintains the integrity of the transmitted data, even in multipath environments. By incorporating the cyclic prefix, OFDM effectively mitigates ISI and enhances the robustness of the communication system. The duration of the guard interval, $T_g \geq \tau_{\max}$, is designed such that it is long enough for the channel to be absorbed within the guard interval, ensuring that the transmission of the OFDM block is not affected. For example, inserting a guard interval T_g =8 µs for a 2 MHz channel leads to a transmission efficiency of $\eta_t = TB/(TB + Tg) = 64/72 \approx 0.89 = 89\%$. Figure 2 illustrates the basic principle of inserting the cyclic prefix.

2.4.1 Mathematical Description of the OFDM Technique

Mathematically, the OFDM signal in the continuous-time domain can be described as follows:

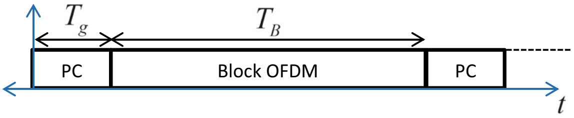


Fig. 2 Insertion of a CP between OFDM blocks

$$s(t) = \sum_i \left[\sum_{k=0}^{N-1} d_{i,k} e^{j2\pi f_k t} \right] \Pi(t - iT_B) \tag{8}$$

The N data symbols $\left\{d_{i,k}\right\}_{k=0}^{N-1}$ are transmitted over N complex sinusoids $\left\{e^{j2\pi f_k t}\right\}_{k=0}^{N-1}$ called subcarriers during the ith block. The spacing $f_k = k/T_B$ between the subcarriers makes them orthogonal over the block interval.

The orthogonality of the subcarriers is mathematically expressed as:

$$\frac{1}{T_B} \int_0^{T_B} \left(e^{j2\pi f_{k_1} t}\right) * \left(e^{j2\pi f_{k_2} t}\right) \mathrm{d}t = \frac{1}{T_B} \int_0^{T_B} \left(e^{j2\pi (f_{k_2} - f_{k_1} t) t}\right) \mathrm{d}t = \begin{cases} 1, \; k_1 = k_2 \\ 0, \; k_1 \neq k_2 \end{cases} \tag{9}$$

where (*), represents the complex conjugate operation.

The pulse shape $\Pi(t)$ has the following expression:

$$\Pi(t) = \begin{cases} 1 \; 0 \leq t < T_B \\ 0 \; ailleurs \end{cases} \tag{10}$$

To visualize the orthogonality of the subcarriers in the frequency domain, we consider the 0th block of the OFDM signal described by equation:

$$s(t) = \sum_{k=0}^{N-1} d_k e^{j2\pi f_k t} \tag{11}$$

The representation in the frequency domain is obtained by applying the Fourier Transform.

$$S(f) = F[s(t)](f) = T_B e^{-j2\pi f T_B/2} \sum_{k=0}^{N-1} d_{i,k} \sin c\left[\left(f - \frac{k}{T_B}\right) T_B\right] \tag{12}$$

where

$$\sin c(x) = \begin{cases} 1 & x = 0 \\ \frac{\sin \pi x}{\pi x} & ailleurs \end{cases} \tag{13}$$

By maintaining adequate spacing between subcarriers, each frequency is rendered frequency-flat. This transforms the frequency-selective wideband channel into N narrowband channels that are non-selective, as the channel behaves as flat within each narrowband. While this approach eliminates inter-symbol interference (ISI), it comes at the expense of a slight reduction in spectral efficiency. On the other hand, OFDM technique can be enhanced over a specific environment conditions by assigning more bits to frequency intervals with stronger gains and fewer bits to those with weaker gains. This adaptive approach, called bit loading, depends on the channel remaining relatively stable to ensure precise measurements. where channel conditions are more predictable, than in high-mobility wireless systems, where rapid changes in the channel make accurate measurement and adaptation more challenging.

2.4.2 Cyclic Prefix

As stated in Sect. 4.1, the inclusion of a guard interval ensures operation free from inter-symbol interference (ISI), provided that a cyclic prefix (CP) is sent within this interval. Over the duration of a single OFDM block period:

$$s(t) = \sum_{k=0}^{N-1} d_k e^{j2\pi f_k t}, \quad 0 \leq t < T_B \tag{14}$$

where $\{d_k\}_{k=0}^{N-1}$ are the data that will be transmitted, $\left\{e^{j2\pi f_k t}\right\}_{k=0}^{N-1}$ represents the N subcarriers used to transmit the data symbols, and T_B is duration symbol. $-T_g \leq t < 0$ is the period of the guard interval, where T_g is the guard time. The insertion of the cyclic prefix consists of transmitting the last subcarriers of the OFDM block during the guard interval.

$$s(t) = \sum_{k=0}^{N-1} d_k e^{j2\pi f_k (t+T_B)} = \sum_{k=0}^{N-1} d_k e^{j2\pi f_k t} e^{j2\pi k} = \sum_{k=0}^{N-1} d_k e^{j2\pi f_k t}, \quad -T_g \leq t < 0 \tag{15}$$

It is important to note that the simplification above is enabled by the periodic nature of the signal. As a result, the OFDM signal, incorporating a guard interval and cyclic prefix, can be concisely represented as:

$$s(t) = \sum_{k=0}^{N-1} d_k e^{j2\pi f_k t}, \quad -T_g \leq t < T_B \tag{16}$$

The signal with a guard interval s(t) could be expressed by:

$$s(t) = \begin{cases} b(t), & -T_g \leq t < 0 \\ \sum\limits_{k=0}^{N-1} d_k e^{j2\pi f_k t}, & 0 \leq t < T_B \end{cases} \tag{17}$$

where b(t) represents the symbols transmitted in the guard interval $-T_g \leq t < 0$.

Note that transmitting the cyclic prefix in the guard interval ensures operation without ISI.

2.4.3 Discrete-Time Model (DT)

To perform numerical simulations using discrete Fourier transforms, it is convenient to define the OFDM signal using a DT model.

First, we begin with the description of the received signal *r(t)* after transmission of *s(t)* through the channel h(t).

The received continuous-time signal is [20]:

$$r(t) = s(t) * h(t, \tau) + n(t) = \int_{-\infty}^{+\infty} h(t, \tau)s(t - \tau)\mathrm{d}\tau + n(t) \tag{18}$$

If the channel is time-varying, the received signal can be expressed as:

$$r(t) = s(t) * h(\tau, t) + n(t) = \int_{0}^{\tau_{\max}} h(\tau, t)s(t - \tau)\mathrm{d}\tau + n(t) \tag{19}$$

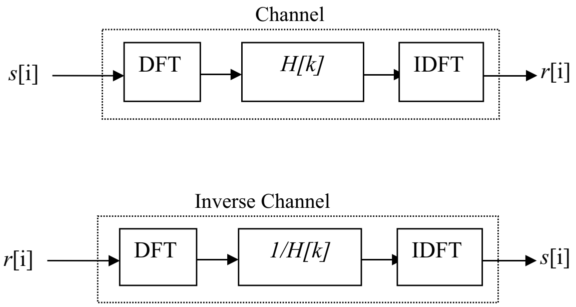
Figure 3 illustrates a synoptic diagram outlining the sample computation process based on Eq. (19). The channel's impact is represented as a Discrete Fourier Transform (DFT) followed by a set of multipliers (H[k]), and then an Inverse Discrete Fourier Transform (IDFT). Additionally, the inverse channel is depicted, which consists of a DFT, a set of multipliers (1/H[k]), and an IDFT. As a result, the transmitted samples s[i] can be accurately reconstructed by processing the received samples r[i] through this inverse channel.

The inverse channel structure depicted in Fig. 3 is designed to correct the alteration introduced by the channel, earning it the name frequency domain equalizer (FDE).

This type of equalizer is applicable only when the channel's effect can be represented as a circular convolution, a condition inherently satisfied by OFDM systems. Figure 4 provides an illustration of the implementation of the FDE in the context of OFDM.

In the specific context of OFDM, modulation is performed using an Inverse Discrete Fourier Transform (IDFT), while demodulation is achieved through a Discrete Fourier Transform (DFT). As illustrated in Fig. 5, the DFT and IDFT effectively cancel each other out, and the resulting block diagram represents the

Fig. 3 The channel in the discrete time domain



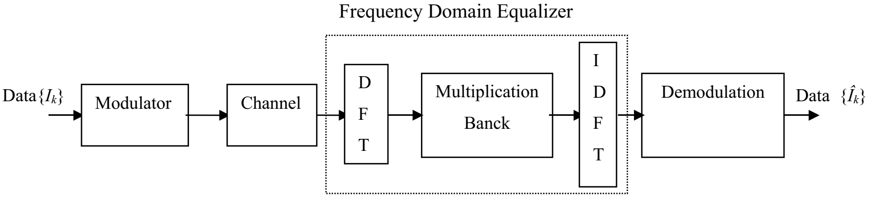
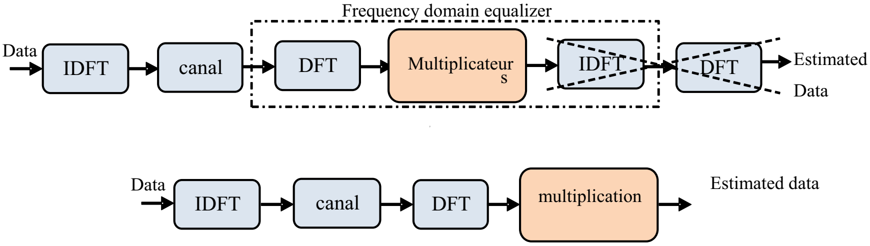

Frequency Domain Equalizer
Data $\{I_k\}$
Modulator
Channel
DFT
Multiplication Banck
IDFT
Demodulation
Data $\{\hat{I}_k\}$

Fig. 4 Modulation/demodulation with frequency domain equalizer


Frequency domain equalizer
Data
IDFT
canal
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IDFT
DFT
Estimated Data
Data
IDFT
canal
DFT
multiplication
Estimated data

Fig. 5 Basic blocks for the transmission/reception of the OFDM signal

standard structure of a conventional OFDM system. It is important to note that the DFT and IDFT effectively withdraw each other, and the consequential block diagram represents the standard structure of a conventional OFDM system.

The set of multipliers following the DFT is commonly known as a single-tap equalizer, which performs a complex multiplication for each frequency slice.

2.5 *Functional Diagram of OFDM*

Figure 5 presents a high-level overview of the OFDM system, whereas Fig. 6 delves into a more comprehensive breakdown of its functional components. The encoder enhances the bit stream by adding redundancy, which facilitates error correction and boosts system reliability.

One of the primary limits of OFDM is its high peak-to-average power ratio (PAPR), which can lead to distortion in the power amplifier. In the subsequent sections, the classification and modeling of power amplifiers, as well as the statistical properties of PAPR, are explored in detail.

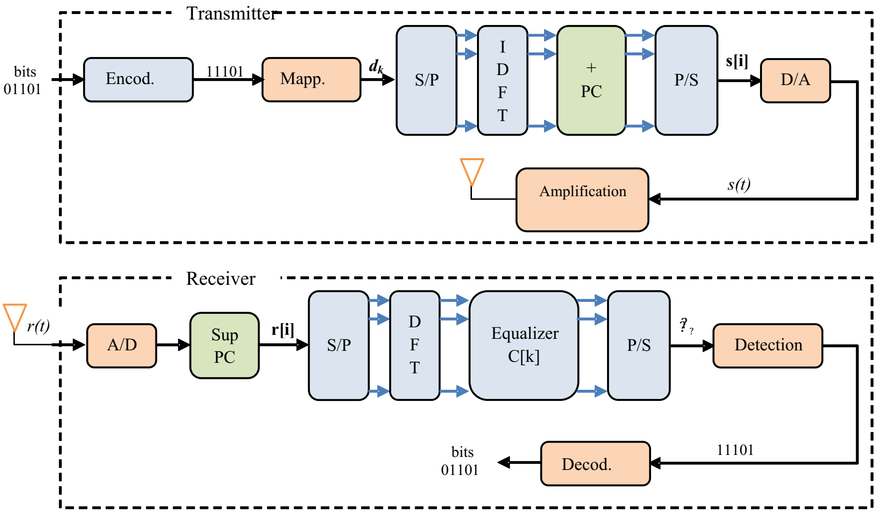

Fig. 6 The functional blocks of OFDM technique

2.6 *Analysis and Statistics of PAPR*

As we mentioned earlier, the OFDM waveform suffers from a high PAPR. Therefore, it is essential to apply PAPR reduction during the processing step before passing the signal through the power amplifier. This is not acceptable to system designers, as they prefer RF power amplifiers to operate with high efficiency.

2.6.1 Power Amplifier: General Overview, Classes, and Models Used

Generally, the space between the transmitter and receiver ranges from a few meters to several kilometers. To transmit a signal over a long distance, it must have sufficient power to propagate. Amplification is the final step performed on the signal at the transmitter. This operation is ensured with the help of a power amplifier. In the ideal case, the amplified signal retains the same shape as the original signal generated by the blocks preceding the amplification stage. In reality, this is not the case, as a power amplifier is made up of active devices (transistors) that are nonlinear.

2.6.2 General Overview of Power Amplifiers

The final part, the most critical regarding energy consumption impacts and potential distortions on the signal, is handled by the power amplifier. Its role is to bring the modulated RF signal to a sufficient level at the transmission antenna. Practically, based on the power balance shown in Fig. 7, the energy (PDC) provided by the

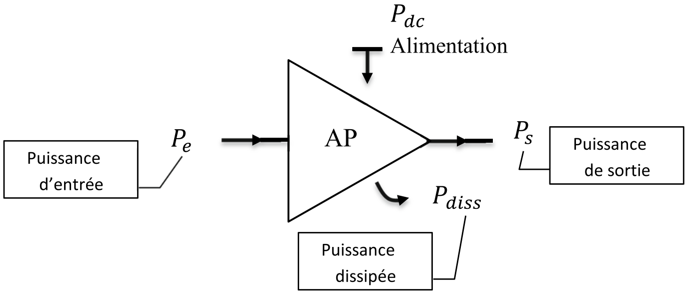

Fig. 7 Power balance in a PA (power amplifier)

power supply is not entirely transmitted to the load. A more or less significant part is dissipated (Pdiss) as heat by the active and nonlinear device (the transistor).

For its design, it is essential to study the phenomena of stability, linearity, and adaptation, and to correct them. To do so, the following requirements must be met:

- The PA (Power Amplifier) is generally the main power consumer in a transmitter. A major design requirement is to determine how efficiently the PA can convert the power supply into RF output power.

The designer often needs to focus on the efficiency of the power amplifier. Note that efficiency results in either lower operating costs (e.g., for a cellular base station) or extended battery life (e.g., for a smartphone). The linearity of the PA is another important requirement. The input/output relationship must be linear to preserve the integrity of the signal. Regardless of the targeted standard or operating class, the main parameters for characterizing a PA are [21]:

- Output power Ps,
- Input power Pe,
- Power supply Pdc,
- Dissipated power Pdiss,
- Power gain Gp,
- Power added efficiency (PAE),
- 1 dB compression point PC1,
- The power balance of the amplifier is given by:

$$P_e + P_{dc} = P_{diss} + P_s \tag{20}$$

The gain in power is given by

$$G_p = \frac{P_s}{P_e} \tag{21}$$

Efficiency serves as a key measure of a power amplifier's (PA) performance. It is determined by comparing the output power (Pout) to the power consumed (Pdc).

The efficiency of an amplifier measures the amount of power supply Pdc converted into output power Ps. Calculating the efficiency provides information about the lost power, P_{diss}.

Efficiency is an important performance indicator for a PA, and it is defined as the ratio between the amplifier's output power (Pout) and the consumed power (Pdc).

$$\eta = \frac{P_s}{P_{dc}} \tag{22}$$

Efficiency is thus strongly related to the operating class of the amplifier. This definition of efficiency does not account for the power supplied to the input of the device. The concept of power added efficiency (PAE) was introduced to address this gap.

The power added efficiency is written as follows:

$$PAE = \eta\left(1 - \frac{1}{G_p}\right) \tag{23}$$

Now, from Eqs. (25) and (26), we get:

$$PAE = \frac{P_s - p_e}{P_{dc}} \tag{24}$$

3 The Operating Classes of a Power Amplifier

When amplifying a signal (modulated for wireless communication), a trade-off must be made between the linearity and the efficiency of the power amplifier (PA). The signal can be amplified either by a linear PA but at the expense of efficiency, or by a high-efficiency PA but at the expense of linearity. These classes are grouped into two categories based on the mode of operation of the transistor: sinusoidal classes and high-efficiency classes. The sinusoidal classes encompass the transistor operating modes where the signals are of sinusoidal types. This category includes classes A, B, AB, and C. The transistor behaves like a current source, and the output power is proportional to the input power. In the category of high-efficiency amplifiers, there are classes D, E, and F. The transistor behaves like a switch: it is alternately a short circuit and an open circuit, and the output power is not a linear function of the input power.

The efficiency of PA depends on the amplifier's design and implicitly on the active component (the transistor). Thus, operational classes of amplifiers are defined based on the type of transistor biasing and its conduction angle [22]. Linear amplifiers, operating in classes A, B, and AB, are appropriate for amplifying signals with non-constant envelopes. Each of these operational classes has specific characteristics and

Table 1 Conduction angle and efficiency of different PA classes

Class	Conduction angle (δ)	Maximum theoretical efficiency
A	360°	50%
AB	$180° < \delta < 360°$	50% to 78.5%
B	180°	78.5%
C	$\delta < 180°$	100%
D and more	Switching ON/OFF	Until 100%

trade-offs in terms of biasing, linearity, and efficiency. Similarly, there are nonlinear amplifiers grouped into classes C, D… H, and S. In this case, these amplifiers are often referred to as amplifiers for constant envelope signals, unaffected by component nonlinearities [22]. Table 1 provides a summary of the conduction angles and theoretical efficiencies for an ideal amplifier, covering all the amplifier classes discussed earlier.

In summary, when linearity is a top priority, Class A amplifiers should be preferred, despite their lower efficiency. While non-sinusoidal amplifier classes offer high performance, their linearity is significantly compromised. As a result, Class AB amplifiers emerge as a balanced compromise, offering a combination of reasonable efficiency, power output, and wideband performance.

4 Simulation Results and Discussion

In this section, we will analyze the performance of the proposed communication system in terms of BER (Bit Error Rate). To do so, we will first simulate the proposed model for the V2V (Vehicle-to-Vehicle) communication channel, which will be used for the simulation of the communication chain based on OFDM modulation. Then, we will study the performance of OFDM modulation on this channel. Indeed, the V2V channel is a wireless communication channel used for data exchanges between vehicles. This type of channel is characterized by complex propagation conditions due to the dynamic and mobile environment in which it operates. The proposed model takes into consideration three parameters (as shown in the Fig. 8). The first parameter is the multipath nature of the V2V channel, as transmitted signals can reach the receiver through multiple paths due to reflections from buildings, other vehicles, or surrounding obstacles. The second parameter is attenuation, which we also consider in the proposed model. On the other hand, to evaluate the performance of the V2V system, we chose to use OFDM modulation. OFDM (Orthogonal Frequency Division Multiplexing) is a multi-carrier modulation technique that divides the frequency spectrum into multiple orthogonal subcarriers. It is particularly well suited for multipath environments, such as the V2V channel, as it helps reduce Inter-Symbol Interference (ISI). This modulation will be evaluated in terms of BER, considering the channel presented in Fig. 8.

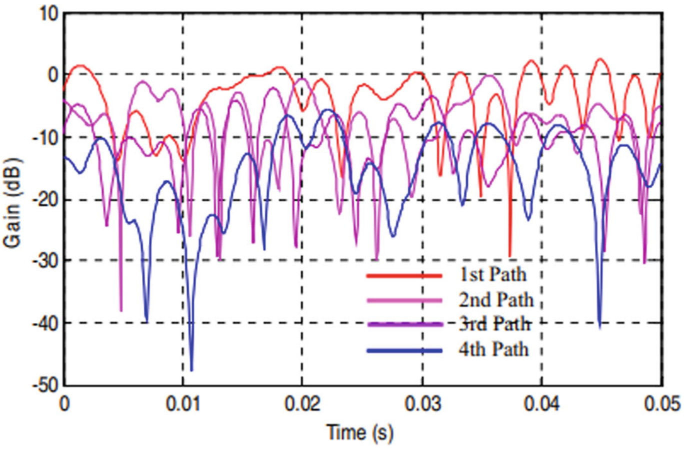

Fig. 8 Proposed multipath channel for V2V communication

The performance of the OFDM-V2V system is evaluated for various V2V channel models, each highlighting different aspects of the system's performance under varying conditions. The specific parameters of the proposed system under investigation are outlined in Table 2, providing a clear reference for the simulation setup. To generate the results, the samples h[i], s[i], and n[i] are created, representing the channel impulse response, transmitted signal, and noise, respectively. Once the received samples are obtained, they are processed by the FDE to mitigate channel-induced distortions, followed by the demodulator to recover the transmitted data. This process ensures a comprehensive evaluation of the system's performance under multipath conditions.

Figure 9 evaluates the performance of OFDM over V2V channel by varying the modulation order M. This analysis provides insights into how changes in modulation order impact system performance. It shown from Fig. 9 that the performance over AWGN outperform the performance of frequency selective channel. This could be explained by the multi-path behavior of the in the frequency selective channel which create inter-symbol-interferences. We can see also as the modulation order increase the BER tends to increase. However, increasing the modulation order mean increasing the data rate of the overall system which mean we have to find a threshold value which

Table 2 Simulation parameters

Parameters	Value
Block period (T_B)	500.10^{-9} s
Number of subcarriers (N)	128
Guard period (Tg)	125.10^{-9} s
Frequency domain equalizer	MMSE
Modulation	QAM, PSK and ASK

allow us to choose which modulation order to attaint which objective. Figure 10 examines the effect of oversampling factor on the performance of the proposed system across two distinct channel models: AWGN and frequency-selective fading with an exponential power delay profile.

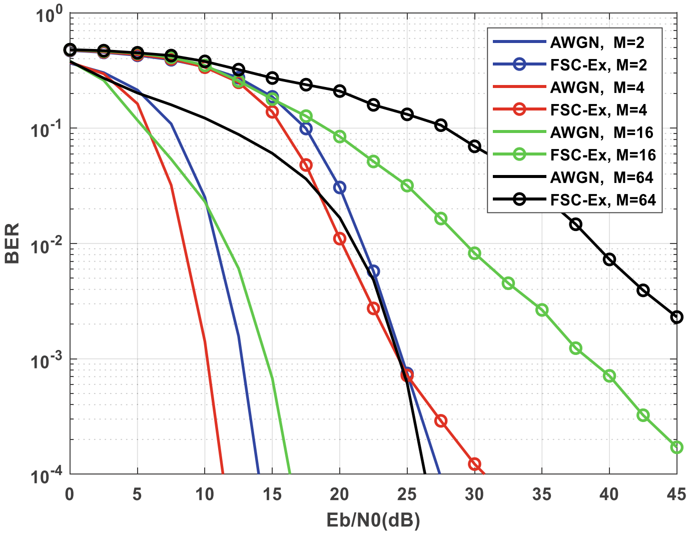

Fig. 9 Performance of OFDM regarding modulation order, using QAM

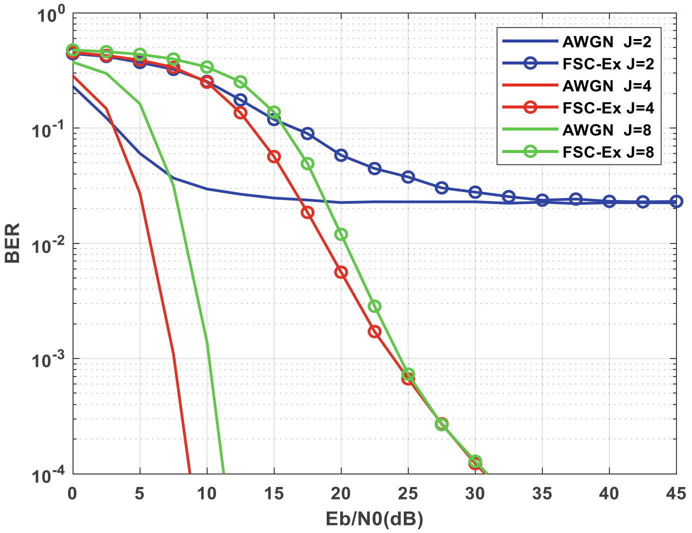

Fig. 10 Performance of OFDM regarding oversampling factor, using QPSK

This comparison reveals how the oversampling factor affects performance in different channel environments, offering a comprehensive understanding of the system's adaptability and robustness under diverse conditions. Together, these figures provide a detailed analysis of the key parameters influencing OFDM system performance. By maintaining a consistent number of subcarriers and following a structured simulation approach, the study provides reliable insights into the performance of the OFDM system in challenging multipath environments which is the main characteristics in V2V channels.

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Based on Figs. 9 and 10, OFDM modulation is a robust solution for V2V communications, capable of handling the challenges of the channel while providing good spectral efficiency. It effectively mitigates the effects of multipath propagation by dividing the transmitted signal into multiple orthogonal subcarriers, reducing ISI and improving signal integrity. Besides, OFDM is well-suited for dynamic and rapidly changing environments, such as those encountered in V2V scenarios, where vehicles are in constant motion and experience varying channel conditions. The performance of the proposed system is evaluated regarding BER which plays a crucial role in assessing the overall performance of the suggested system. By evaluating BER under different channel conditions, we can identify the optimal modulation parameters, such as subcarrier spacing, coding schemes, and power allocation, to enhance communication reliability for a real world channel. Moreover, BER analysis helps in understanding the impact of channel impairments, such as Doppler shifts and fading, allowing for the implementation of adaptive techniques that can further improve the overall performance of the V2V system.

5 Conclusion

Through extensive performance evaluation, the findings demonstrate that OFDM with QAM modulation consistently achieves better spectral efficiency, lower BER, and improved resilience to channel impairments compared to OFDM-QPSK. The superiority of OFDM-QAM makes it the most suitable choice for V2V communication, as it effectively balances data rate, error performance, and spectral efficiency. The insights gained from this analysis provide valuable guidance for optimizing V2V communication systems, contributing to the development of more reliable and efficient vehicular networks. Future work may explore the integration of advanced error correction techniques and adaptive modulation strategies to further enhance V2V communication performance under real-world conditions.

References

1. El Madani, S., Motahhir, S., El Ghzizal, A.: Combination between internet of vehicles and advanced driver assistance systems: overview and description. Multimed. Tools Appl. (2024). https://doi.org/10.1007/s11042-024-20486-3
2. Gorges, H.: Self-assessment of mobility behaviour: quantifying the divergence between self-assessment and vehicle sensor data. Eur. Transport Stud. **2**, 100011 (2025). https://doi.org/10.1016/j.ets.2024.100011
3. Zhu, J., Cui, Y., Mu, J., et al.: Radio resource management for OFDM-based dual-function radar-communication: sum-rate and fairness. J. Wireless Com. Netw. **2024**, 18 (2024). https://doi.org/10.1186/s13638-024-02343-x
4. Li, X., Zhou, Y., Zhao, S., et al.: Photonics joint radar and communication system using dual-band LFM-based signals with opposite chirp polarities. Opt. Quant. Electron. **56**, 1273 (2024). https://doi.org/10.1007/s11082-024-07224-7
5. Jiang, F., Deng, H., Zhang, L.: Periodic event-triggered control for inter-vehicle communications. Int. J. Control. Autom. Syst. **21**, 1285–1295 (2023). https://doi.org/10.1007/s12555-022-0128-2
6. Pedrosa, P., Dinis, R., Castanheira, D., Silva, A., Gameiro, A.: Channel tracking and equalization for UAV communications. In: Jayakody, D.N.K., Muthuchidambaranathan, P., Dinis, R., Panic, S. (Eds.), Integration of Unmanned Aerial Vehicles in Wireless Communication and Networks. Unmanned System Technologies. Springer, Cham (2023). https://doi.org/10.1007/978-3-031-03880-8_1
7. Zhao, Y., Dai, L., Zhang, J., et al.: Near-field communications: theories and applications. Front. Inform. Technol. Electron. Eng. **25**, 1575–1579 (2024). https://doi.org/10.1631/FITEE.2440000
8. Belkadid, J., Benbassou, A., El Ghzaoui, M.: PAPR reduction in CE-OFDM system for numerical transmission via PLC channel. Int. J. Commun. Ant. Propag. **3**(5), 267–272 (2013)
9. Mestoui, J., El Ghzaoui, M., Hmamou, A., Foshi, J.: BER performance improvement in CE-OFDM-CPM system using equalization techniques over frequency-selective channel. Procedia Comp. Sci. **151**, 1016–1021 (2019). https://doi.org/10.1016/j.procs.2019.04.143
10. Narayana, N., Sure, P., Bhuma, C.M.: Experimental investigations on the applicability of LASSO based sparse recovery for compressively sensed OFDM channel estimation. Sādhanā **49**, 133 (2024). https://doi.org/10.1007/s12046-024-02444-9
11. Singh, S., Joshi, S.: Non-pilot based carrier frequency offset estimation and reflection coefficient optimization for RIS-assisted OFDM systems. Phy. Commun. **66**, 102457 (2024). https://doi.org/10.1016/j.phycom.2024.102457

12. Béchadergue, B., Shen, W.-H., Tsai, H.-M.: Comparison of OFDM and OOK modulations for vehicle-to-vehicle visible light communication in real-world driving scenarios. Ad Hoc Netw. **94**, 101944 (2019). https://doi.org/10.1016/j.adhoc.2019.101944
13. Yang, Y., Bai, Z., Pang, K., Liu, H., Gong, P., Ji, Y., Zhang, L.: Performance analysis of cooperative multi-relay spatial modulation based OTFS system in V2V communication. Veh. Commun. **44**, 100687 (2023). https://doi.org/10.1016/j.vehcom.2023.100687
14. El Ghzaoui, M., Das, S., Lenka, T.R., Biswas, A.: Terahertz wireless communication components and system technologies. In: Terahertz Wireless Communication Components and System Technologies, pp. 1–310 (2022). https://doi.org/10.1007/978-981-16-9182-9
15. Li, Z., An, T., Dong, B., et al.: Event-triggered V2V communication-based cooperative adaptive tracking control for nonlinear vehicle platoon systems with unknown lag time. Nonlinear Dyn. **113**, 519–532 (2025). https://doi.org/10.1007/s11071-024-10155-3
16. Raj, D., Ather, D., Sagar, A.K.: Advancing vehicular Ad-Hoc network solutions in emerging economies: a comparative analysis of V2V protocols through simulation studies. SN Comput. Sci. **5**, 1077 (2024). https://doi.org/10.1007/s42979-024-03411-1
17. Kuzulugil, K., Tugcu, Z.H., Cavdar, I.H.: A proposed V2V path loss model: log-ray. Arab. J. Sci. Eng. **48**, 14901–14911 (2023). https://doi.org/10.1007/s13369-023-07922-6
18. Liang, X., Shi, X., Cao, W., et al.: Performance analysis of NOMA-V2V cooperative systems with outdated CSI and imperfect SIC. Wireless Pers. Commun. **134**, 2159–2181 (2024). https://doi.org/10.1007/s11277-024-11005-6
19. Mestoui, J., El Ghzaoui, M.: A survey of NOMA for 5G: implementation schemes and energy efficiency. In: Lecture Notes in Electrical Engineering, vol. 745, pp. 949–959 (2022). https://doi.org/10.1007/978-981-33-6893-4_86
20. EL Ghzaoui, M., Mestoui, J., Hmamou, A., Elaage, S.: Performance analysis of multiband on–off keying pulse modulation with noncoherent receiver for THz applications. Microw. Opt. Technol. Lett. **64**(12), 2130–2135 (2022). https://doi.org/10.1002/mop.33051
21. Kazimierczuk, M.K.: RF power amplifiers, vol. 1. Wiley Online Library (2008)
22. Kenington, P.B.: High linearity RF amplifier design. Artech House, Inc. (2000)